Distrust and Cryptocurrency Price Deviations*

Bo Tang† Yang You‡ Yulin Zhong§

May 18, 2023

Abstract

Cryptocurrency prices differ across countries, and cryptocurrency price deviations fluctuate widely over time. Our paper suggests that distrust toward domestic authorities can explain the dynamics of cryptocurrency price deviations. The local cryptocurrency prices rise after an outbreak of a financial crisis, political scandal, or socioeconomic event that undermines confidence in the domestic government or economy. With panel regressions, we show that Bitcoin price deviations increase by 1.8% when attention to institutional failures rises by one standard deviation. These price responses are much stronger in countries with lower trust levels and during periods with tighter capital controls.

JEL-Classification: G12, G15, M14.

Keywords: Cryptocurrency, Trust, Limits of Arbitrage, Price Deviations, Institutional Failures

*We wish to thank Andrea Carnelli, Jon Danielsson, Daniel Ferreira, Charles Goodhart, Robin Greenwood, Keyu Jin, Christian Julliard, Dong Lou, Igor Makarov, Robbie Minton, Daniel Paravisini, Kenneth Rogoff, Andrei Shleifer, Liliana Varela, Dimitri Vayanos, Luis Viceira, David Yermack, Gloria Yu, Kathy Yuan, Jinyuan Zhang and the seminar participants at the Chinese University of Hong Kong, Harvard University, London School of Economics, Pantheon, Peking University, and the University of Hong Kong, International Conference on Smart Finance (ICSF 2022) for their helpful comments and suggestions. First Draft: December 10, 2020.

†Luohan Academy of Alibaba Group; tangbo@alibaba-inc.com.

‡The University of Hong Kong, Faculty of Business and Economics; yangyou@hku.edu.

§The University of Hong Kong, Faculty of Business and Economics; u3588057@connect.hku.hk.

Since the function of government in issuing money is no longer one of merely certifying the weight and fineness of a certain piece of metal, but involves a deliberate determination of the quantity of money to be issued, governments have become wholly inadequate for the task and, it can be said without qualifications, have incessantly and everywhere abused their trust to defraud the people ... We have no choice but to replace the governmental currency monopoly and national currency systems.

— F.A. Hayek. *The Denationalisation of Money*

1 Introduction

The prominent economist Friedrich Hayek advocated the denationalization of money, arguing that governments "have instantly and everywhere abused their trust to defraud the people" (Hayek (1978)). Cryptocurrency supporters frequently refer to Hayek's view and argue that distrust in centralized authorities is the primary justification for Bitcoin and other decentralized tokens. Is there any empirical evidence that supports or runs contrary to this view?

In this paper, we study the changes in local cryptocurrency price deviations—that is, the ratio of the cryptocurrency price in a local currency, converted into dollars at the real-time exchange rate, to the average worldwide dollar price—as an indicator of crypto demand movement over time.[1] Makarov and Schoar (2020) document the frequent occurrence of price deviations in many countries and highlight that the capital controls make prices differ across countries. We test whether distrust of the government can increase the local crypto price deviations using a data set of Bitcoin and Ethereum trading from 31 countries.

We first identify domestic economic and political events from January 2015 to January 2020 that induce distrust of the government and examine the price deviation changes in

[1]Two fundamental premises of this paper: First, demand for cryptocurrency is not directly observable; thus, we need to investigate the price deviations for evidence. Second, cryptocurrency trading has significant frictions, so arbitragers cannot immediately equalize prices on exchanges in all countries. In Appendices C and D, we discuss the limits of arbitrage in cryptocurrency trading, various costs of cross-country arbitrage, and other legal risks of trading crypto in different countries.

response to these events. To obtain the event list, we start with the Google Trends index of the keywords "conflict," "crisis," "instability," and "scandal" in these 31 countries and manually look up actual events around all search peaks for these four keywords. Notably, our sample period is a generally tranquil period of economic growth and financial stability. We only discovered three major crises in our sample: Brazil's economic slowdown, the Chinese stock market crash in 2015, and the severe devaluation of the Argentine peso in 2018.[2] In Argentina, we find that the Bitcoin price premium rose to above 20% after capital controls were tightened in September 2019 in response to the peso's depreciation. In China, the Bitcoin price deviations rose over 2% in the eight weeks after the largest single-day loss on August 24, 2015, and the Chinese government embarked on a sequence of actions to penalize foreign capital and ban short-selling financial instruments. In general, domestic cryptocurrency price deviation increases when there is a local economic crisis outbreak, particularly after the government imposes more limitations on capital flow in and out of the country.

Next, we consider price responses to political events. Using Google Trends data, we identify 43 political events that drew massive public attention: 15 corruption scandals involving top politicians, 9 outbreaks of political protest, and 19 other forms of social unrest. The local Bitcoin price deviation was 2.00% ($s.e.$=0.56%) higher, and the Ethereum price deviation was 1.78% ($s.e.$=0.41%) higher on average in the eight weeks after the event was known to the public. Domestic cryptocurrency investors increased demand and temporarily drove up prices when they decided that local political authorities had lost credibility.[3] Some other search peaks unrelated to trust are concerned with natural disasters and economic slowdowns (food shortages, drought, and energy crises), while other search peaks were irrelevant events, such as the sex scandals of pop stars in the country. These events do not systematically weaken the credibility of the government, and we correspondingly see little impact of these

[2] Neither the World Bank nor the IMF offers an official definition of regional economic and financial crises officially defined by the World Bank or IMF. Thus, we cross-validate our three events with Wikipedia's economic crisis list . The 2014–2017 Brazilian economic crisis, the 2015 Chinese stock market crash, and the Argentine monetary crisis all fall under our purview because Google Trends can identify their impact. The 2018 Turkish currency crisis is excluded, as our cryptocurrency price data does not cover the Turkish Lira.

[3] Carlson (2016) provides narrative evidence-based interviews that cryptocurrency does play a role in evading capital controls. The cryptocurrency's popularity is mainly attributable to the high-level historical inflation, corruption, and other factors that disappoint domestic fiat currency users.

events on cryptocurrency price deviations.

To complement our event studies, we further estimate the price responses to public attention to economic and political failures using the entire panel data. We construct the institutional failure attention index (IFA henceforth) as the principal component of "conflict," "crisis," "instability," and "scandal" in Google Trends. Notably, our estimation with the panel data is a lower bound for the true impact as some attention is not associated with the domestic authority. One core finding is that the deterioration of institutional quality drives local Bitcoin prices up: a one-standard-deviation increase in IFA corresponds to a 1.79% (*s.e.*=0.68%) higher Bitcoin prices and 1.21% (*s.e.*=0.43%) higher Ethereum price. The same effect also holds for all four keywords: a one-standard-deviation increase in searchers for "conflict" corresponds to a 1.49% (*s.e.*=0.65%) increase in the Bitcoin price deviation; similarly, increases of 0.67% (*s.e.*=0.32%) are seen for "crisis," 1.25% (*s.e.*=0.60%) for "instability," and 0.87%(*s.e.*=0.40%) for "scandal." In parallel, we find that trading volume modestly rises concurrently. Also, the search volume of keywords "Bitcoin" and "Ethereum" on Google increases during escalated attention to institutional failures. These empirical findings suggest that higher local price deviations are likely driven by an increased domestic interest in buying cryptocurrencies.

Lastly, we further show that the price deviation response to the IFA depends on the country's trust level in the country. Our baseline trust measure comes from the Global Preference Survey (GPS), which asks respondents whether they assume other people have good intentions.[4] We cross-validate our trust measure with the World Value Survey and find that it is strongly correlated with higher confidence in local institutions (civil service, government, banks, etc.) and lower perceived corruption in governments and civil services. The price deviation response is mainly concentrated in low-trust countries and diminishes or even disappears in high-trust countries: a one-standard-deviation increase in IFA corresponds to a 3.05% (*s.e.*=1.61%) higher Bitcoin price and a 1.97% (*s.e.*=0.74%) higher Ethereum price in 11 low-trust countries, but only a 0.31% (*s.e.*=0.36%) higher Bitcoin price and a 0.04% (*s.e.*=0.36%) higher Ethereum price in the high-trust countries. Similarly, IFA has much stronger explanatory power for the time-varying cryptocurrency price deviations in the low-

[4]See Falk et al. (2018) for a more detailed description of the Global Preference Survey.

trust countries, particularly Argentina (R-squared=23.8%) and Mexico (R-squared=20.1%), and the explanatory power is almost zero in high-trust countries. One concern is that trust elicited in GPS might be correlated with other economic factors. To address this concern, we further horse-race trust with GDP, financial credit, the rule of law, government effectiveness, and control of corruption, and we show that trust is the most powerful indicator for explaining the heterogeneous response to IFA.

Our empirical results suggest that distrust-induced cryptocurrency demand is behind the larger price deviations over worldwide dollar prices. We further rule out several possible alternative mechanisms. First, simultaneous and future fiat currency depreciations are unlikely to explain IFA-induced local cryptocurrency price increases. In the panel data, the local currency's exchange rate (and its changes) cannot explain the cryptocurrency price deviation responses to the IFA. In addition, the price premium also cannot forecast further currency returns. Second, the drying up of liquidity is not the reason for the widened price deviations. We find that trading volume modestly increases after outbreaks of political scandal and when the IFA is elevated. The local cryptocurrency price rises are more likely to be driven by stronger domestic demand rather than a reduction in the cryptocurrency supply. Lastly, we show that our results remain unchanged when we control for the openness of capital accounts, and the price responses are greater in periods when the government tightens the capital controls. The capital control is what causes large price deviations to persist without being arbitraged away immediately in cryptocurrency trading.

Our paper is closely related to three strands of the literature. First, we contribute literature on Bitcoin price deviations and the limits of arbitrage in cryptocurrency trading.[5] Makarov and Schoar (2020) pioneering paper is the first to study price differences across currencies systematically. Several papers investigate why price deviations exist and persist. Choi et al. (2022) argues that capital controls and Bitcoin micro-structure jointly explain the Bitcoin price premium in Korea, and Hautsch et al. (2018) argue that blockchain settlement

[5] A vast body of literature studies the limits of arbitrage in other financial markets. De Long et al. (1990), Shleifer and Vishny (1997), Gromb and Vayanos (2002), and Gromb and Vayanos (2018) investigate how arbitrage costs sustain mispricing. Rosenthal and Young (1990) and Froot and Dabora (1999) examine pairs of Siamnese-twin stocks in different markets around the world with identical claims of cash flow but different prices. Mitchell et al. (2002) and Lamont and Thaler (2003) provide evidence of the price differences in the stocks of a parent company and its subsidiaries.

latency contributes to the limits to arbitrage. The remaining question is: what factor drives the price deviation changes over time, given the limits of arbitrage? Makarov and Schoar (2020) document widening deviations during a Bitcoin price rally. Yu and Zhang (2022) shows that Bitcoin price deviations increase with higher policy uncertainty. Our paper mainly focuses on events and episodes when local authorities' actions harmed their credibility.

Our research is also related to studies on trust and finance. Trust broadly affects investment decisions and shapes financial contracts (e.g., Guiso et al. (2008), Guiso et al. (2004), Guiso et al. (2006), Guiso et al. (2013), Sapienza and Zingales (2012), Gennaioli et al. (2022), and Caporale and Kang (2020)). Recent work argues that trust plays a critical role in financial intermediation and is crucial for stock market participation; see Gennaioli et al. (2015), Dorn and Weber (2017), Gurun et al. (2018) and Kostovetsky (2016). Our paper envisions the other side of the importance of trust in finance: Distrust induces the demand for cryptocurrencies.

Our paper also contributes to the discussion of alternative monetary systems. Hayek (1978) argues that governments can defraud people and abuse their trust; thus, he advocates private bank money. The recent literature has focused on blockchains and discussed their potential applications to de-nationalized currency issuance (Harvey (2016), Budish (2018), Biais et al. (2019), Ferreira et al. (2022), Cong and He (2019), Cong et al. (2021), Abadi and Brunnermeier (2018), Easley et al. (2019), Sockin and Xiong (2020), Catalini and Gans (2020)), the role of cryptocurrency in the monetary system (Yermack (2015), Schilling and Uhlig (2019), Danielsson (2019)), and other forms of private money(You and Rogoff (2022)).[6] Our findings show that distrust of the domestic government feeds the demand for de-nationalized money.

Our paper is organized as follows. Section 2 describes the data sources and price deviations of cryptocurrency. Section 3 presents a series of event studies of major economic disasters, financial crises, and political scandals from 2015 to 2020 and quantifies their price impacts. Section 4 presents panel regressions of cryptocurrency price deviation on a time-varying institutional failure attention index constructed from Google Trends and explores

[6] In addition to private money, Auer et al. (2020), and Auer and Böhme (2020) examine Central Bank Digital Currency (CBDC) as an alternative monetary system.

heterogeneous responses in terms of cross-country trust level. Section 5 rules out alternative explanations, as our findings are not driven by local fiat currency depreciation, liquidity, or changes in capital controls. Section 6 concludes the paper.

2 Data Description and Price Deviations

2.1 Cryptocurrency Price Deviations

We obtain volume-weighted Bitcoin and Ethereum daily prices quoted in different fiat currencies from the *CryptoCompare.com* API service.[7] We use the daily exchange rate obtained from Bloomberg to compute the local cryptocurrency prices converted into U.S. dollars and currency returns.

The Bitcoin prices quoted in different fiat currencies, converted into dollars with prevailing exchange rates, vary from country to country. On January 5, 2020, the Bitcoin price was 8,024.58 USD. However, Bitcoin traded at 11,101.39 USD equivalent (578,501.76 pesos) in Argentina, meaning that Argentine investors were willing to pay a 38% premium on that date. We define the price deviation as the price markup relative to the Bitcoin dollar price:

$$Deviation_{c,t} = \frac{Prc_{c,t} \times Exchange_{c-USD,t}}{Prc_{USD,t}} \times 10000$$

$Prc_{c,t}$ is the price in the local currency of country c, and $Exchange_{c-USD,t}$ is the exchange rate from Bloomberg.[8] In the robustness check, we construct the price deviations from the cryptocurrency prices quoted in euro rather than dollar prices. We obtain five years (January 2015 - January 2020) of cryptocurrency prices (ETH prices are only available since August 2015) and trading volumes from CryptoCompare.[9] $Deviation_{c,t}$ has the unit of basis point and should always equal 10000 if the law of one price holds perfectly in all countries.

[7] *CryptoCompare.com* compute the cryptocurrency prices by aggregating crypto-fiat currency trading pairs from different exchanges by the trading volume. See for the API service we use.

[8] Cryptocurrency trading in USD has the largest trading volume and is also supported by most mainstream crypto-exchanges. We use the Bitcoin price in USD as the global benchmark price.

[9] CryptoCompare calculates daily cryptocurrency prices based on the 24-hour volume-weighted average among local exchanges. 24-hour volumes are calculated solely based on transaction data.

Bitcoin price deviations can be astoundingly large. Figure A.1 plots the price deviations in Argentina and the United Kingdom from 2015 to 2020. During the 2018 Argentine monetary crisis, the maximum price gap in that country reached 37.14% in January. The price difference was only 2.16% in the United Kingdom at the same time. Argentine Bitcoin prices are also much higher and more volatile than the U.K. Bitcoin prices over time. Table 1 Panel A presents the summary statistics of price deviations across 31 countries in our sample. The average price deviation across all countries is 3.26%, and the standard deviation is 13.25%. Argentina is the country with the most expensive Bitcoins: it is 12.07% more expensive on average to buy Bitcoins there than in the United States. Colombia has the cheapest Bitcoins: they are 3.51% cheaper than U.S. Bitcoins on average. Moreover, BTC and ETH price deviations are 90.98% correlated, and such this high correlation implies that a country-specific component drives the time-varying price deviations, consistent with Makarov and Schoar (2020).[10]

2.2 Institutional Failures

We use weekly Google Trends indices of the keywords "conflict," "crisis," "scandal," and "instability" to capture time-varying attention to institutional failures. The maximum of an index scales to 100 given the sample period from January 2015 to January 2020. We run two sets of analyses with these four Google Trends indices. First, we manually look up all search peaks for our four keywords and construct a database for the event studies, as presented in Section 3. Some events might hurt domestic institutional quality, such as financial crises, corruption scandals, and some political events, while other events are irrelevant to local institutions, such as drought, pollution, or pop star sex scandals. Second, we use the principal component analysis (PCA) to extract a time-varying composite index to capture the domestic attention to institutional failures and analyze its relationship with price deviations in the panel data in Section 4.

[10] We present the trend of the median number of price deviation of BTC and ETH in Figure A.2. The trend for BTC's median number of price deviations is also highly correlated.

2.3 Trust and Other Country Characteristics

To explore cross-country heterogeneity, we obtain a set of country characteristics. Trust data are taken from the Global Preference Survey (GPS).[11] This survey asked respondents whether they assume that other people only have the best intentions, which captures the general distrust level. We obtain other more granular trust-related variables — confidence in various local institutions and perceived government corruption— from the World Value Survey (WVS) to validate our baseline trust measure. In the WVS, each respondent provides their confidence level in banks, companies, government, politics, and civil service. We assign a score 2 to "A great deal of confidence," 1 to "Quite a lot confidence," -1 to "Not very much confidence," -2 to "None at all," and 0 to "Don't know" or "No answer." For each country, we use the average score from all of the respondents in the country to proxy for the confidence level. Similarly, for each question about perceived corruption in business, civil service, and local and state government, we assign a score of 2 to "None of them," 1 to "Few of them," -1 to "Most of them," -2 to "All of them," and 0 to "Don't know" or "No answer". Perceived corruption control is the average score of the respondents in each country.

The capital control measure is based on the Chinn-Ito index, which measures a country's degree of capital account openness. It is constructed from binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions. For each country in our sample, we obtain its yearly data on capital openness so that the capital control measure is in the panel data format. We also obtain cross-sectional country features. Data on GDP per capita, and credit by the financial sector are from the World Development Index. The rule of law, government effectiveness, and corruption control scores are from Worldwide Governance Indicators.

We match price deviations by currency with Google Trends indices, trust data, exchange rate, trading volume, cryptocurrency returns, capital control, and country features. There are 31 countries (excluding the U.S.) left in our sample: Argentina, Australia, Brazil, Canada,

[11] The Global Preferences Survey is a globally representative survey of 80,000 individuals on risk and time preferences, positive and negative reciprocity, altruism, and trust in 76 countries worldwide. See Falk et al. (2018). The trust level ranges from -1 to 1.

Chile, China, Colombia, Croatia, the Czech Republic, Hungary, India, Indonesia, Israel, Japan, Kenya, Mexico, Pakistan, the Philippines, Poland, Romania, Russia, Saudi Arabia, South Korea, Sweden, Switzerland, Thailand, Ukraine, the United Kingdom, the United Arab Emirates, Vietnam, and South Africa.

3 Event Studies

We manually look for the events around the Google search spikes of the keywords "'conflict," "crisis," "instability," and "scandal." for all countries. In total, we find 122 Google search spikes, and we report them in Appendix B. We successfully identify 95 events, while the other 27 peaks cannot be associated with any news. Of these 95 events, 78 events out of 95 are directly related to local institutions or politics. Almost no domestic search spike is linked to international news or events in other countries. The other 17 events are irrelevant to institutional quality; these include sexual scandals involving pop stars, corrupt sports teams, etc. We further classify all 122 spikes into four categories and study price deviations related to: (1) three major economic and financial crises, (2) political scandals, (3) other social-economic events, and (4) irrelevant and other unknown events .[12]

3.1 Major Economic and Financial Crises

In our sample period from 2015 to 2020, we only find three economic and financial crises, as this was a tranquil growth period after the global economy recovered from the Global Financial Depression: These are Argentina's monetary crisis, the Chinese stock market crash, and Brazil's economic slowdown are under our radar.[13]

[12] Appendix B also lists the Google Trend peaks that cannot be linked to any event with our best effort.

[13] https://en.wikipedia.org/wiki/List_of_economic_crises provides a list of economic crises, and it confirms all three crises identified with a Google search. Wikipedia also lists the Turkish currency and debt crisis in 2018; however, we do not have cryptocurrency price quoted in Turkish lira.

3.1.1 Argentina's Monetary Crisis and Capital control

In 2017, the annual inflation rate in Argentina reached 25%; meanwhile, the Federal Reserve of the United States raised interest rates from 0.25% to 1.75% and then to 2%. Argentina's peso depreciated dramatically and triggered a currency crisis. On September 1, 2019, Argentina's central bank announced new restrictions on foreign currency transactions. Mauricio Macri, the President of Argentina, required the companies to seek central bank permission to purchase foreign currency and to make transfers abroad. He also limited individuals to purchasing a maximum of USD 10,000 per month. The Chinn-Ito capital account openness index dropped from 1.549 in 2018 to -0.726 in 2019. Cryptocurrency provides an instrument for domestic peso holders who wish to evade the tightened capital controls or who simply want to hold an asset not subjective to peso depreciation. Thus, cryptocurrency becomes more desirable to domestic investors, particularly when Argentinians find it hard to exchange the peso for the U.S. dollar. Figure 1 shows that the BTC and ETH price deviations increased from 6% to 13% after the tightening of the capital control on September 1st, 2019. In a placebo test, we do not find any simultaneous price premium change in the all-country median.

We further examine Argentina's capital control policy over time and find that capital account liberalization started in 2015. Back in 2011, the government, led by Cristina Fernández de Kirchner, restricted the purchase of U.S. dollars by forbidding the practice except in a limited number of cases. From 2012 to 2015, the Chinn-Ito index held steadily at -1.93. On December 17, 2015, the government, led by Mauricio Macri, lifted the currency controls and allowed the peso to float when markets opened to increase exports and spur economic growth. The Chinn-Ito index also indicates that capital control persistently eased until the currency crisis in 2019, as the index values were -1.234 in 2016, 1.295 in 2017, and 1.549 in 2018. Figure A.3 plots the premium in the 16-week time window around December 13, 2015. The BTC and ETH price deviations steadily dropped from about a 53% premium in October 2015 to 3% in February 2016 in response to loosening capital controls.[14]

[14] Our finding here is consistent with that of the cross-country analysis by Alnasaa et al. (2022) that cryptocurrencies can be used to circumvent capital controls.

3.1.2 The 2015 Chinese Stock Market Crash

The Google Trends "crisis" peaked in China on August 2015, and the timing corresponds to the Chinese stock market bubble. The SSE composite index fell by 8.48% on August 24, 2015, after the Chinese government took many actions to stabilize the capital market but failed to stop the stock prices from freefalling. August 24 marked the largest single-day drop since the Global Financial Crisis in 2008.

The panic that burst the Chinese stock bubble began with an -2% single-day return of the SSE Composite Index on June 15, 2015. On June 28, the People's Bank of China, the Chinese central bank, announced a decrease of benchmark interest rates for RMB loans and deposits at financial institutions by 0.25% in an attempt to rescue the market, as the index had by then declined by a further 20%. The Chinese government also took several legal actions against practitioners and government officials judged to be accountable for the market collapse.[15] To limit the market meltdown, the government limited the freedom to sell Chinese stocks and made shorting-selling more costly or even impossible in the derivative market.[16] The price drop and unpredictable changes in trading restrictions frustrated investors and added more uncertainty to the domestic capital market.

We plot the price deviations around August 24 in Figure 2, and we find that Bitcoin and Ethereum were traded relatively more expensively than international prices after the stock market crash, by roughly 2%. The price increase cannot be explained by investor sentiment or speculation, as Chinese stocks were dramatically devalued in this time window. Also, there is no sign of changes in capital control in response to the stock market crash (the raw Chinn-Ito index (*kaopen*) is a constant -1.234 from 2015 to 2020). Our evidence suggests

[15] On July 3, 2015, the state-owned Chinese media outlet *Financial News* posted an article, "No time to lose in the fight against malicious short-selling." Meanwhile, the China Financial Futures Exchange started to examine accounts that made short-selling bets. On the same date, Qingfeng Meng, Vice Minister of Public Security of the People's Republic of China, collaborated with China Securities Regulatory Commission to investigate reports of malicious selling of stocks and stock indices. By August 30th, the Chinese regulators had arrested 197 people, including Xiaolu Wang, a journalist at Caijing Magazine (a leading independent financial media), and several government officials in China Securities Regulatory Commission (the Chinese stock market regulator), for spreading "rumors" about the stock market crash.

[16] On July 31, Shanghai Stock Exchange and Shenzhen Stock Exchange announced trading restrictions on 10 accounts identified with significant unusual trading behavior. On August 1, the China Securities Regulatory Commission announced that it had taken restrictive trading measures on 24 accounts that engaged in algorithm trading and blamed foreign capital for triggering the market crash. On the evening of August 2, Citadel confirmed that its account had been restricted from trading by the Shenzhen Stock Exchange.

that pessimism about capital market governance increased cryptocurrency demand.

3.1.3 Brazil's Economic Recession

We identified Brazil's economic recession with the Google search for "crisis" beginning in June 2014. The Brazilian GDP decreased from 2.46 trillion to 1.8 trillion Brazilian real from 2014 to 2016. Meanwhile, the unemployment rate increased from 6.7% to 11.6%, and inflation rose from 6.3% to 8.7%, respectively. Figure 3 plots the trend of Bitcoin price deviations and relates them to the (normalized) exchange rate and Brazilian GDP from April 2015 to April 2017[17] in Brazil. The Brazilian GDP and currency both dropped quickly from April 2015 to February 2016. The cryptocurrency price deviations remained high from November 2015 to June 2016, when the currency started to appreciate and the GDP stabilized.

We run the following time-series regression to examine the relationship between the price deviations and the Brazilian real exchange rates.

$$Deviation_{c,t} = \beta Curindex_{c,t} + \gamma_c + \epsilon_{c,t} \tag{1}$$

Table A.1 shows that the cryptocurrency deviations are negatively correlated with the normalized exchange rate of the Brazilian real. In Column (1), the naive time-series regression implies that 1% depreciation corresponds to a 10.80-bps ($s.e. = 4.27$) higher BTC premium and 11.07-bps ($s.e. = 5.14$) higher ETH premium. In Column (2), we add the simultaneous Brazilian currency return to the regression, and we find that the coefficients of the exchange rate index remain stable: 11.61 bps ($s.e. = 4.20$) for BTC and 12.84 bps ($s.e. = 5.12$) for ETH. Cryptocurrency prices in Brazil are very inefficient as the simultaneous currency return has a roughly 40% pass-through (39.64% for BTC and 42.75% for ETH) to the cryptocurrency price deviations. Thus, the fiat currency depreciation itself would mechanically drive the price deviations down instead of pushing them up; therefore, the currency depreciation itself cannot explain any of the increase in price deviations as it generates. In Column (3), we add the quarterly GDP to the regressions and document that 1% depreciation corresponds to 11.72 bps ($s.e. = 4.37$) for BTC and 14.42 bps ($s.e. = 5.61$)

[17] The quarterly GDP gradually grew by 4% from quarter 1 in 2017 to quarter 4 in 2019.

for ETH conditional on the GDP level. A GDP decline also positively contributes to higher price deviations with limited statistical power. Our evidence suggests that a radical currency depreciation could boost an excessive cryptocurrency demand sufficiently to offset its downward pressure on local Bitcoin and Ethereum prices.

Our keyword search approach does not identify any specific event or policy changes in Brazil (the Chinn-Ito index has held at -1.234 since 2015).Yu and Zhang (2022) study three political crises in Brazil: Operation Car Wash, which resulted from a leak on March 17, 2014; the Brazil Labor Reform proposed on December 23, 2016; and the protests against reforms that erupted on March 15, 2017. Figure A.4 plots the gap between the Bitcoin price deviation and global median deviation within the eight weeks following each event date. The gap between the Bitcoin price deviation of Brazil and the market median became larger within two weeks after each event. The price deviation gap jumped from -2% to 3% in the week of March 17, 2014, and further to 10% in the next eight weeks for Operation Car Wash. Brazilian president, Michel Temer proposed labor reform to combat unemployment and economic recession on December 23, 2016. In the week that the labor reform proposal was submitted to the Chamber of Deputies, the gap jumped from 2% to 8%, but it quickly reverted to the pre-reform level in the next three weeks. The labor reform was controversial, as many critics argued that it violated the Brazilian constitution and international labor conventions. An outbreak of protests outbreak against labor reform occurred on March 15th, 2017. In the wake of the protests, the gap jumped from 1% to 7% and drifted up to 15% after eight weeks. These results are consistent with the event studies in Yu and Zhang (2022).

3.2 Political Scandals

In addition to the three crises studied above, we find 43 events related to politics and manually validate whether these political events are bad news that impairs government credibility. Among them, 14 events are corruption scandals, 9 are outbreaks of political protest, and 16 are other forms of social unrest.[18]

[18]The remaining four events would not induce distrust: Thailand's crackdown on corruption in March 2017, the Qatar–Saudi Arabia diplomatic conflict (identified in the UAE in June 2017 and Saudi Arabia in August

For each event, we track the changes in price deviation in an event window of 16 weeks. Figure 4 plots the average (equal-weighted) price deviation of all 43 political events. We find a consistent pattern in which the price deviations of BTC and ETH (solid lines) drift after the Google search spikes. As a placebo test, we also plot the median price deviations of all of the countries (dashed lines) in the same time window of these political events. We find no significant rise or a much smaller increase in the all-country median price deviation. In Figure 4 shows that local cryptocurrency prices started to rise before the event date as the largest search volume on Google is typically later than the onset of the political event. One example is the Marawi Conflict in the Philippines: the attention on Google reached the highest level six weeks after the war began. Figure A.5 shows that cryptocurrency price deviations rallied significantly after the war began but fluctuated after the Google search peak. These mis-specified event dates might explain the pre-trend and lead us to underestimate the price impacts of these political events, and our estimates provide a lower bound.[19]

Table 2, Column (1) reports the price deviation event studies of political events in a regression format. There is an average of 199.86 bps (*s.e.* = 56.45) higher Bitcoin price deviations and 177.57 bps (*s.e.* = 50.96) higher Ethereum price deviations in the eight weeks after the event date. Cryptocurrency prices became higher when domestic investors witnessed political scandals and had less confidence in their home country.

We further run several robustness checks. First, we compute the adjusted price deviations as the raw price deviations minus the international median price deviation that week and replicate the same event studies. The BTC-adjusted deviations rose by 137.05 bps (*s.e.* = 41.43), and ETH-adjusted deviations rose by 101.35 bps (*s.e.* = 33.03). These coefficients are statistically significant with a slightly smaller magnitude. Then, we further exclude the four events that do not induce distrust and report the results in Table A.2. Price deviations increased by 203.493 bps (*s.e.* = 56.45) for BTC and 174.81 bps (*s.e.* = 54.72) for ETH.[20]

2017 with Google Trends), the ceasefire deal between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC) in July 2016.

[19]In addition, some events might not be significant enough to change the price deviation in that country. One example is the Indian-Pakistan Conflict. Figure A.6 shows the trend of Bitcoin price deviation from January 25, 2015 to May 17, 2015 in India and Pakistan. Bitcoin became roughly 10% more expensive in Pakistan during the conflict, while the price deviations did not move much in India. Given that India is much larger than Pakistan, the same conflict may trigger more panic in Pakistan than in India.

[20]We plot the four political events that do not induce distrust in Figure A.7. The price deviations do not

Last, we re-estimate the coefficients with deviations against euro crypto prices in Table A.3 and obtain similar results: 199.92 bps ($s.e = 55.78$) for BTC and 152.52 bps ($s.e = 48.60$) for ETH.

We also find that attention to cryptocurrency increased after the outbreaks of these political events. Table A.4, Column (1) reports the event studies of the Google Trends indices of "Bitcoin" and "Ethereum". The index increases by 5.09 ($s.e.$=2.04) units for political events, corresponding to a 0.34 standard deviation more attention to Bitcoin on Google; similarly, the coefficient is 6.41 ($s.e.$=2.61), 0.37 standard deviations more attention to Ethereum. People also pay more attention to gold but with a much smaller magnitude: 1.19 ($s.e.$=0.68) units correspond to only a 0.08 standard deviations increase in the eight weeks after the event.

3.3 Other Keyword Search Peaks

There are other keyword search peaks, which we further classify these peaks into socioeconomic events, irrelevant events, and other unknown events. Overall, we do not find significant price reactions.

3.3.1 Other Socioeconomic Events

We identify 11 other socioeconomic events and classify them into two event groups depending on whether the event is related to the government. Five events are associated with the government: the UAE economy slowdown reported in December 2017, the Brazilian sovereign credit rating downgrade in December 2015, the Colombian peso depreciation in August 2015, the severe economic downturn in India in December 2019, and the Indian stock market crash in February 2016. Table 2, Columns (2) and (3) report the regression analyses of events related and unrelated to the government and not associated with the government on price deviations, respectively. For events related to the government, there is an average of 216.37 bps ($s.e. = 70.31$) higher Bitcoin price deviations and 236.39 bps ($s.e. = 85.51$) higher Ethereum price deviations in the eight weeks after the event date. There are six

systematically increase after these four events.

events unrelated to the government: the illegal migrant crisis in Australia in June 2015, U.S. President Trump's steel tariffs on Brazil in December 2019, the British homelessness crisis in November 2017, the Indian milk crisis in June 2015, the drought in Kenya in June 2019, and the subsequent Kenya food crisis in December 2019. There are no significant increases in BTC and ETH prices in the eight weeks after these event dates.[21] Consistent with our findings for political events, we only find positive price impacts for events tied to domestic authorities.

3.3.2 Irrelevant and Unknown Events

We also identify 17 events not related to economics and politics. These irrelevant events include five sex scandals, five company scandals, three environmental crises, two sports scandals, and two other unclassified events. Table 2, Column (3) shows almost no price impacts of these 17 events. We further break down our analysis by event type and study the impact of each kind on cryptocurrency price deviation. Figure A.9 shows the trend of Bitcoin price deviation after eight weeks of the start date of these five types of events separately. The Bitcoin price deviations modestly increase but are not statistically significant after company scandals and environmental crises. We find no price deviation changes after the sex and sports scandals. Consistent with our prior analysis, we see no distinguishable price deviation increases as these events have little to do with distrust toward the government. Then, we show the trend of Bitcoin and Ethereum price deviation around 8 weeks of the start date of irrelevant events in Figure A.10 and find that the price deviation does not increase much after the event date.

Still, 17 search peaks cannot be associated with any event after our best manual search on Google. There may be no actual event associated with the index surge (pure noise in the data). It may also be possible that no news in English is available on Google. We show the average price deviation of Bitcoin and Ethereum respectively around 8 weeks of the start date of unknown events in Figure A.11 and find that the price deviation for both cryptocurrencies does not change much after the event date. Table 2, Column (4) indicates

[21] Figure A.8 plots the event studies of socioeconomic events related to government and those not related to government. We do not find local cryptocurrency price rises for government unrelated events.

that the price deviations of cryptocurrencies would not significantly increase after the dates of Google Trends search peaks.

4 Panel Regressions

In this section, we extend our analysis to the full panel data. We wish to answer the question of whether attention to institutional failure contributes to the rise of local Bitcoin prices.

4.1 Institutional Failures

We construct the institutional failure attention (IFA) index from the Google Trends indices for "conflict", "crisis," "instability," and "scandal" to capture the time-varying concerns about the domestic institutional quality. Our event studies show that these keywords successfully capture events associated with distrust toward the government. Google Trends data also pick up some noise (e.g., sports and sexual scandals) that do not undermine trust in government, which tends to bias our estimation toward zero. Thus, our panel data analysis tends to provide lower bounds for the true effect.

To smooth out the Google Trends, we first compute the cumulative Google Trends index $GT_{c,t}$ as a discounted sum of Google search indices in the past eight weeks with a discount factor of 0.8.[22,23]

$$GT_{c,t} = \sum_{i=0}^{i=7} 0.8^i \times Google_{c,t-i}$$

Then, we run a principal component analysis (PCA) on the cumulative Google Trends index of "conflict," "crisis," "instability," and "scandal," and we take the first component as the institutional failure attention index (IFA).[24] Lastly, to make the coefficients interpretable, we normalize IFA and all $GT_{c,t}$ by their means and standard deviations.

[22]Our results are not sensitive to the choice of the discount factor of 0.8. As Table A.5 shows, our baseline results hold for other deflators from 0.2 to 1.

[23]$Google_{c,t}$ denotes the raw Google Trend index for country c and week t.

[24]Table A.6 reports the correlation of the IFA and cumulative Google Trends index for the four keywords.

In our baseline specification, we regress cryptocurrency price deviations on IFA and cumulative Google search indices one by one. To set a high bar for statistical significance, we report two-way clustered standard errors at both currency and week levels and adjust for heteroskedasticity in all of the regressions throughout the paper.

$$Deviation_{c,t} = \beta IFA_{c,t} + \gamma_c + \epsilon_{c,t} \tag{2}$$

Table 4 reports the results of our baseline regressions. In Panel A, a one-standard-deviation increase in IFA corresponds to a BTC price deviation increase of 179.00 bps($s.e.$=68.18). The BTC price deviation expands by 149.78 bps ($s.e.$=64.67), 67.09 bps ($s.e.$=32.26), 125.198 bps ($s.e.$=60.41), and 87.50 bps ($s.e.$=39.70) when the search indices of "conflict," "crisis," "instability," and "scandal" rise by one standard deviation, respectively. In Panel B, the ETH price deviations yield similar responses: a one-standard-deviation increase in IFA corresponds to 121.15 bps ($s.e.$=43.12) higher local ETH prices. The local cryptocurrency prices tend to be relatively higher in episodes when investors are more concerned about domestic institutional quality.

We run three sets of robustness checks. Makarov and Schoar (2020) documents that price deviations tend to be more prominent when Bitcoin prices rise. First, we add the cryptocurrency returns in the past eight weeks to our baseline regression in Table A.7 column (2). Consistent with Makarov and Schoar (2020), the price deviations increase when cryptocurrency prices appreciate; however, the coefficients of IFA almost do not change much: from 179.00 bps ($s.e.$=68.18) to 172.60 bps ($s.e.$=68.33) for Bitcoin, and from 121.15 bps ($s.e.$=43.12) to 111.52 bps ($s.e.$=47.10) for Ethereum. [25] Second, our cryptocurrency price deviations are endogenous to the exchange rate currency return might affect the price deviation as the exchange rate is crucial for constructing price deviations. Table A.7 columns (3) and (4) report robustness check results when controlling cryptocurrency returns. The coefficients and significance also remain quite similar: 179.38 bps ($s.e.$=68.12) after controlling for the exchange rate index and 160.52 bps ($s.e.$=55.24) after controlling for simultaneous

[25] In Table A.8, we control cryptocurrency return in regressions of Google search indices of "conflict," "crisis," "instability," and "scandal". Institutional failures still predict a surge in price deviation. The coefficients are smaller as a cryptocurrency price rally also partially explains the domestic interest in cryptocurrency.

currency returns for Bitcoin; 121.12 bps ($s.e.$=43.08) after controlling for the exchange rate index and 119.22 bps ($s.e.$=42.17) after controlling for simultaneous currency returns for Ethereum. These results indicate that our findings of IFA are orthogonal to crypto and currency returns.[26] In a third robustness check, we use the price deviation from the crypto prices quoted in euro and replicate the same set of specifications. As shown in Table A.9, the coefficients are similar to our baseline results, indicating that U.S. cryptocurrency dollar price movements do not drive our results.

How persistent is the price deviation response? Figure 5 plots the IFA coefficients β_k of predicting price deviations in the next 30 weeks by estimating the following regression:

$$Deviation_{c,t+k} = \alpha + \beta_k IFA_{c,t} + \epsilon_{c,t}$$

The coefficients gradually decay over time and decline to zero in the next 20 weeks. Thus, the IFA impacts tend to be transitory, and arbitrageurs can slowly synchronize the local crypto prices with the international prices. We further discuss the limits of arbitrage in Appendix C and D, and these frictions prohibit local crypto prices from equalizing with the international U.S. dollar price upon the arrival of distrust events.

4.2 Attention to Cryptocurrency

Parallel to the analysis of event studies, Table 5 reports the impact of institutional failures on attention to Bitcoin and Ethereum in Google Trends. We construct $\Delta GT\_Bitcoin_t = \frac{8 \times GT\_Bitcoin_t}{\sum_{i=1}^{i=8} GT\_Bitcoin_{t-i}}$ as the number of Google searches relative to the past eight-week average. Column (1) shows that if the IFA index increases by one standard deviation, the Bitcoin and Ethereum Google searches would increase by 7.7% ($s.e.$=2.3%) and 17.3% ($s.e.$=4.4%), respectively. Columns (2) - (5) show consistent results that attention to cryptocurrency is

[26] In Column (5), the coefficients are 155.48 bps ($s.e.$=55.44) for BTC and 111.65 bps ($s.e.$=46.37) for ETH after controlling for both crypto and currency returns.

also greater when local people search for these four keywords in a higher volume.[27,28]

4.3 Distrust and Price Response Heterogeneity

We further examine the role of trust in explaining the price response heterogeneity across countries. Based on the trust score from the Global Preference Survey, we divide all 31 countries in our sample into three groups: 11 high-trust countries ($Trust \in [0.2, 1)$), 9 medium-trust countries ($Trust \in [-0.1, 0.2)$), and 11 low-trust countries ($Trust \in [-1, -0.1)$). In addition, we define the variable *Distrust* as

$$Distrust = 1 - Trust$$

Table 6, Columns (2) - (4) report our baseline regressions from Eq.(2) by country trust category. A one-standard-deviation increase in IFA predicts a Bitcoin price deviation increase of 304.81 bps (*s.e.*=160.80) in low-trust countries and of 242.712 bps (*s.e.*=132.32) in medium-trust countries, but will have no impact, 31.02 bps (*s.e*=35.82) in high-trust countries. This pattern is similar to Ethereum — a one-standard-deviation increase in IFA predicts the Bitcoin price deviation increases of 196.65 bps (*s.e.*=73.71) in low-trust countries, 203.42 bps (*s.e.*=77.52) in medium-trust countries, and 3.96 bps (*s.e.*=35.89) in high-trust countries. In Column (5), we include the interaction term of IFA and *Distrust* and run the following regression:

$$Deviation_{c,t} = \beta_1 IFA_{c,t} + \beta_2 Distrust_c \times IFA_{c,t} + \gamma_c + \epsilon_{c,t}$$

The coefficient β_2 is 427.31 (*s.e*=201.94) for Bitcoin and 228.49 (*s.e*=126.71) for Ethereum, implying that price responses are stronger in low-trust countries. Investor countries with lower trust levels are prone to chase cryptocurrencies more when concerns about institutions are exacerbated. Table A.12 presents the results for the cumulative Google search indices

[27]In Table A.10, we add Bitcoin and currency return to regressions. Institutional failures still predict a surge in "Bitcoin" Google searches by 6.0% (*s.e.*=1.5%) and 10.3% (*s.e.*=3.6%). The coefficients are smaller as a cryptocurrency price rally also partially explains the domestic interest in Bitcoin.

[28]Table A.11 reports the results for Google searches on "gold," and we find no evidence that IFA triggers higher search volumes about "gold".

on the four keywords ("conflict," "crisis," "instability," and "scandal"), which show that the price responses are more pronounced in low-trust countries, particularly for "conflict" and "crisis."[29]

Trust may correlate with many other country features (e.g., Zak and Knack (2001)). We horse-race distrust with other vital aspects ($Feature_c$) of a country, including GDP per capita, credit by the financial sector, the rule of law, government effectiveness, and corruption scores.[30] Table 7 reports the horse-racing regressions:

$$Deviation_{c,t} = \beta_1 IFA_{c,t} + \beta_2 Distrust_c \times IFA_{c,t} + \beta_3 Feature_c \times IFA_{c,t} + \gamma_c + \epsilon_{c,t}$$

Column (1) reports the result of the original specification (as in Table 6, Column (5)), and Columns (2) - (6) show the horse-race results with the five country features. For Bitcoin, the credit-to-GDP ratio takes β_2 down the most, only from 427.31 ($s.e.$=201.94) to 399.742 ($s.e.$=183.00). Similarly, the rule of law reduces β_2 for Ethereum the most, only from 228.49 ($s.e.$=126.71) to 185.89 ($s.e.$=128.05). The β_2's magnitude and statistical significance remain mostly unchanged when we control these five features, and we find that β_3 is never economically meaningful. The horse-race regressions confirm that distrust delivers unique explanatory power and cannot be easily overruled.[31]

Then, we further evaluate the explanatory power of IFA in price deviation and see how it affects the trust level. To make countries comparable, we scale price deviations to a "mean zero, standard deviation one" distribution $\widehat{Deviation_{c,t}}$ for each country-cryptocurrency[32], and we estimate the country-specific β_c and R-squared (pooling Bitcoin and Ethereum observations together) in the following regression:

$$\widehat{Deviation_{c,t}} = \beta_c IFA_{c,t} + \gamma + \epsilon_{c,t}$$

[29] Table A.13 shows the robustness check results with the price deviations from the EUR crypto price; the results are consistent.

[30] GDP and financial credit (% GDP) are from the World Development Index; the rule of law, government effectiveness, and corruption scores are from Worldwide Governance Indicators.

[31] Table A.14 shows the robustness check with price deviations from EUR crypto price. and

[32] The normalized price deviation is the raw deviation minus the country-level average and divided by the variance of price deviation, that is, $\widehat{Deviation_{c,t}} = \frac{Deviation_{c,t} - \overline{Deviation_c}}{Var(Deviation_c)}$.

Figure A.12 Panel A plots the β_c against each country's trust level, and we can see a clear negative relationship with slope -0.42 ($s.e.$=0.17). A one-standard-deviation change in IFA is expected to induce a 0.5-standard-deviation move of the price deviation in a country with the lowest trust level (about -0.5). For a country with the highest trust level (about 0.5), the IFA score is expected to be uncorrelated with the price deviation changes.

We also find a robust negative relationship with slope -7.39 ($s.e.$=3.50) between the R-squared and the trust level. In Argentina and Mexico, IFA provides the highest explanatory power, with an R-squared of over 20%. As shown in Figure A.13 and A.14, Argentina and Mexico also report very high perceived corruption and a lack of confidence in civil service and governments. News of institutional failure news is a more powerful predictor of cryptocurrency price deviation in countries where people have a worse perceived institutional quality.

5 Discussion

In this section, we first validate our trust variable with survey questions from the World Value Survey (WVS) on confidence in local authorities and perceived corruption. Then, we investigate and try to rule out alternative explanations related to trading volume, exchange rates, and capital controls.

5.1 Economic Foundations of Distrust

Does our distrust measure capture the lack of confidence in local institutions? We correlate GPS trust with measures of confidence in institutions and perceived corruption in various organizations from the World Value Survey.[33]

WVS elicits respondents' confidence levels in banks, major companies, government, politics, and civil service and reports the percentage of respondents in each of the four categories

[33] WVS runs seven waves of its survey. The countries covered in each wave are slightly different. Our analysis prioritizes the data from the latest wave (Wave 7). For the countries not covered by Wave 7, we use the data from Wave 6, and so on. 17 countries in our sample can be found in WVS. GPS provides a much more extensive country coverage than WVS.

of confidence level. We assign a weight of 2 to "A great deal of confidence," 1 to "Quite a lot of confidence," -1 to "Not very much confidence," -2 to "None at all," and 0 to "Don't know" or "No answer." The country-specific confidence score is the weighted average of the respondents in each category. Similarly, WVS surveys perceived corruption in business, civil service, and local and state governments. We assign a weight of 2 to "None of them," 1 to "Few of them," -1 to "Most of them," -2 to "All of them," and 0 to "Don't know" or "No answer." The corruption control score is the weighted average of the respondents in each category. The scale of the score ranges from -200 to 200.

Trust is positively correlated with confidence in institutions. Figure A.13 and Table A.15 show that a one-unit increase in GPS trust predicts 112.70 points ($s.e. = 47.01$) more confidence in banks, 50.83 ($s.e. = 24.18$) for companies, 128.08 ($s.e. = 41.99$) for government, 108.1 ($s.e. = 41.72$) for politics, 117.0 ($s.e. = 31.67$) for civil service, and 119.25 ($s.e. = 38.35$) for justice.

People who distrust more also believe that corruption is more common. Figure A.14 and Table A.15 report the relationship between trust and the perceived control of corruption in business, civil service, and local and state government. Trust corresponds to a lower perception of corruption: the regression coefficient of perceived corruption on trust is 65.17 ($s.e. = 30.37$) for business corruption, 85.10 ($s.e. = 39.00$) for corruption in civil services, 100.87 ($s.e. = 44.85$) for national/state government corruption, and 69.73 ($s.e. =36.37$) for local government corruption, respectively.[34]

[34] As Falk et al. (2018) confirms that the trust measure in GPS is consistent with the WVS, we also validate the correlation between GPS trust and WVS trust in our country sample. WVS provides questions regarding general trust in most people, in people you know personally, in your neighbor, and in people you first meet. As before, we assign the weight of 2 to "Trust completely," 1 to "Trust somewhat," -1 to "Do not trust very much," -2 to "Do not trust at all," and 0 to "Don't know" or "No answer." We define the country-level WVS trust score as the weighted average of the respondents in each category. Table A.15 shows that a one-unit increase in the GPS trust measure corresponds to 20.92 ($s.e. = 10.42$) higher score of the questions "most people can be trust", 67.13 ($s.e. = 34.24$) higher trust to people you know personally, 60.38 ($s.e. = 26.10$) higher trust in neighbor, and 46.24 ($s.e.= 30.65$) higher trust in people you first met, respectively. The R-Squared values of the above regressions are 13.43%, 15.47%, 20.31%, and 9.78% for these four trust questions. These results confirm that the trust measures in GPS and VWS are broadly consistent, and GPS provides better country coverage.

5.2 Trading Volume

Is it possible that a liquidity shortage might drive up local cryptocurrency prices? We find that trading volume increases modestly when the IFA is elevated. The trading volume is insufficient to explain the price deviation change. As cryptocurrencies gained in popularity after 2015, trading volume rose in most countries; thus, we use the following two metrics to scale the trading volume. First, we compute volume share as the percentage of trading volume in the local country as a percentage of the global total trading volume. Second, we define volume growth as the ratio of raw volume to the past eight-week average trading volume.

We first revisit the event studies. Figures A.15 and A.16 plot the event study on Bitcoin and Ethereum's volume share and growth for political events and government-related socioeconomic events, respectively. In all of the figures, we do not observe any drop in trading volume in either the level or growth rate. Table A.16 reports the pre and post changes in trading volume: the Bitcoin volume share is only 3% ($s.e.$=3%), and volume growth is 8.9% ($s.e.$=5.1%)higher. We also find a modest increase by 0.1% ($s.e.$=0.01%) in the volume share of Ethereum upon government-related socioeconomic events.[35]

Next, we investigate trading volume in the panel data. In Table A.17, we report the effect of the IFA and Google Search Index on ΔVol and Vol_Share. Most of the coefficients are positive but not statistically significant, which means that institutional failure attention is modestly positively correlated with the trading volume of cryptocurrencies. Then we also control the ΔVol and Vol_Share in the Eq.2 and report the regression results in Table A.18. The results show that the coefficients would not change significantly when we control the volume compared with Table 4.

Next, we replicate our baseline results conditional on the trading volume and check whether our results only hold for periods when liquidity is limited. In Table A.19, we experiment with subsamples with weeks with positive volume (not zero or missing values) reported in Column (2), weeks with trading volume above the 25^{th} percentile in Column

[35]For events that do not move the price premium, we also do not find either the volume share or volume growth of Bitcoin and Ethereum.

(3), weeks with trading volume above the median trading volume in Column (4), and weeks with the largest trading volume above the 75^{th} percentile in Column (5). For Bitcoin, a one-standard-deviation increase in IFA corresponds to 165.88 ($s.e.$=67.27), 193.57($s.e.$=73.13), 111.92($s.e.$=42.31), and 100.54 ($s.e.$=44.28) bps increase in price deviation in these four subsamples respectively. Similarly, for Ethereum, a one-standard-deviation increase in IFA leads to 115.72 ($s.e.$=43.12), 147.34 ($s.e.$=42.05), 140.44 ($s.e.$=34.73), and 94.49 ($s.e.$=41.43) bps increases in price deviation in these four subsamples, respectively. A higher IFA still induces an increase in the price deviation, even in the quartile with the largest volume.

These results suggest that liquidity shortage is unlikely to be the reason for the widening price difference. On the contrary, the volume is modestly larger when attention to institutional failure is greater; thus, arbitrageurs could make the market more efficient. However, we still observe a significant increase in price deviation. Moreover, our results hold when we control trading volume and different trading volume thresholds. Therefore, liquidity is unlikely to be the driving force for price deviation changes.

5.3 Exchange Rates

The exchange rate is an essential variable for price deviation construction. We first evaluate whether exchange rate changes affect the price deviation. Figure A.17 plots the coefficients of uni-variate regressions of price deviation on lead and lagged exchange rate returns. We find that one-week lagged and simultaneous currency appreciation contributes to the increase in price deviation: a one-bps increase in the exchange rate translates into a 0.2 bps increase in price deviation. The response shrinks to 0.1 bps with two-week lagged exchange rate returns and almost zero with more lags. For any shock in the exchange rate, about 20% passes into price deviation simultaneously and takes about two to three weeks to fade away. The relationship itself illustrates the limited arbitrage in cryptocurrency trading.

Do exchange rate impacts contaminate our empirical identifications? The short answer is no. We add the currency exchange rate index[36], and simultaneous currency returns to the

[36]The index is the cumulative log currency returns, starting from January 2015. The index measures the relative exchange rates in our sample period.

main specifications in Appendix Table A.7. The coefficients do not change much: the Bitcoin price deviations rise by 179.38 bps (*s.e.*=68.12) when we control for simultaneous currency return, 160.52 bps (*s.e.*=55.24) after controlling for the exchange rate and Ethereum price deviations rise by 121.12 bps (*s.e.*=43.08) when we control for simultaneous currency return, 119.22 bps (*s.e.*=42.17) when we control for the exchange rate. Consistent with Figure A.17, exchange rate returns do positively predict the price deviations, but orthogonal to the factors that we document in Section 5.

We further explore whether Bitcoin price deviations can predict anything in the currency markets. First, we relate Bitcoin price deviations to the covered interest parity (CIP) deviations (Du et al. (2018)). Table A.20, Column (1) reports the univariate regression but does not identify any relationship with CIP deviations. In Columns (2)-(5), we check whether Bitcoin price deviations predict any currency depreciation or appreciation. We also find no evidence that Bitcoin price deviations predict anything in the future one week, eight weeks, or 24 weeks in the future. Moreover, a high-rise price deviation does not indicate a higher probability of a fiat currency crisis, defined as a 15% depreciation in the following 24 weeks. Our results imply that Bitcoin price deviations mostly come from the factors determining Bitcoin demand but contain little information on FX markets.

5.4 Roles of Capital Controls

Many barriers can arise in this procedure and prevent arbitragers from acting. It is often argued in the literature that capital controls are the primary reason for price deviations across countries.[37]. This section investigates the role of capital control in driving price deviation.

Since September 2019, Argentine companies have been subject to a central bank rule that requires them to repatriate all export earnings and convert them into pesos at the official exchange rate set by the central bank. Further, companies must obtain central bank approval to access U.S. dollars. Simultaneously, as shown in Figure A.1, the Argentine Bitcoin price surged to 40% more expensive than the U.S. dollar price when the central bank tightened

[37]See, e.g., Makarov and Schoar (2019) Makarov and Schoar (2020), Yu and Zhang (2022), Choi et al. (2022)

the capital controls in Argentina.

Under tight capital controls, institutional arbitragers would face more challenges when sending money out of the country and might not convert local currencies to USD at a desirable exchange rate. To quantify capital controls, we adopt the dataset compiled by Chinn and Ito (2006), in which they construct an index measuring a country's degree of capital account openness. It is based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

Table 8 reports the analysis of capital control change (annually updated capital openness index) and cryptocurrency price deviation. A one-unit increase in capital closeness corresponds with 1,931.354 and 999.012 bps in the price deviations of Bitcoin and Ethereum, respectively. Controlling IFA, we can see from Column (3) that capital closeness has predictive power for price deviation, with the coefficients dropping to 1,864.816 and 906.407, respectively. Our findings confirm that capital control matters for price deviation. More importantly, as shown in Column (4), the correlation between IFA and price deviation is larger in countries with tighter capital control. Therefore, the institutional failure channel that drives price deviation is more pronounced in more constrained countries.

6 Conclusion

This paper provides suggestive evidence that distrust toward domestic politics or economic situations drives up the local cryptocurrency price premium relative to the prevalent dollar price. The premium response is notably more prominent in low-trust countries than high-trust countries. Domestic sentiment toward cryptocurrency is most likely to be the driver of these widened price deviations, as people search more than usual for "Bitcoin" and "Ethereum" more on Google than usual when the IFA is high. At the same time, we find little evidence that cryptocurrency premiums predict currency depreciation or economic downturns.

Market segmentation and capital controls are both necessary for the phenomena to exist.

The predictability of IFA gradually diminishes to zero within 20 weeks, indicating that cryptocurrency arbitrage is slow-moving for most non-US/EUR currencies (thus, the widened price deviations are transitory). The price deviation responses are also stronger in the periods when the country imposes tighter capital controls than usual.

Our findings suggest that the fundamental value of cryptocurrency partially contributes to the distrust of local institutions. The peer-to-peer network attracts domestic investors more, particularly when the country's fragile domestic financial system and corrupt politics become more salient to the public or the government tries to place more limits on financial freedom. Cryptocurrency can potentially weaken capital controls or restrictive domestic economic policies as investors can always store their wealth in cryptocurrency, particularly in countries and periods of time when people have low trust in local authorities.

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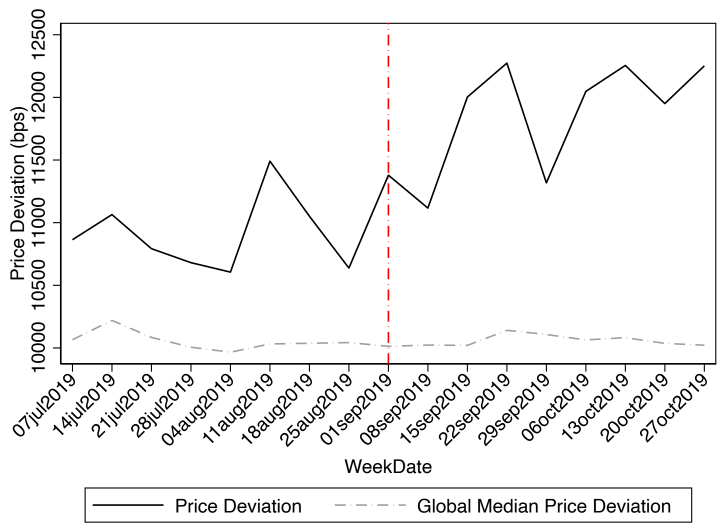
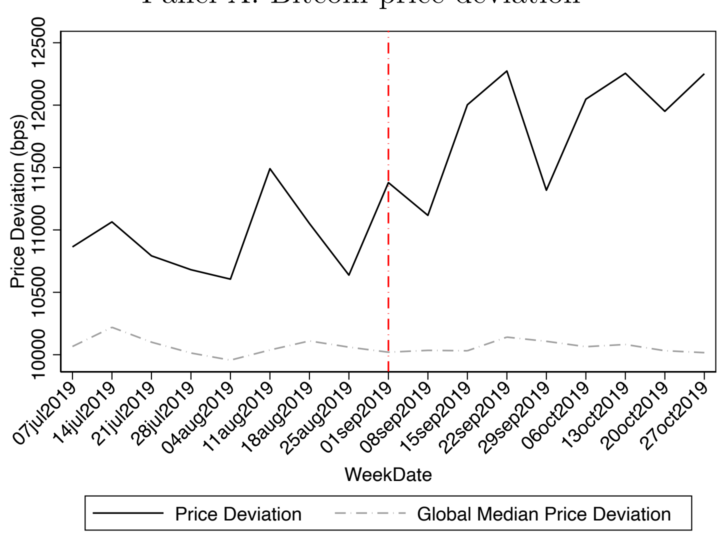
Figures and Tables

Figure 1: Argentina's monetary crisis and additional capital control



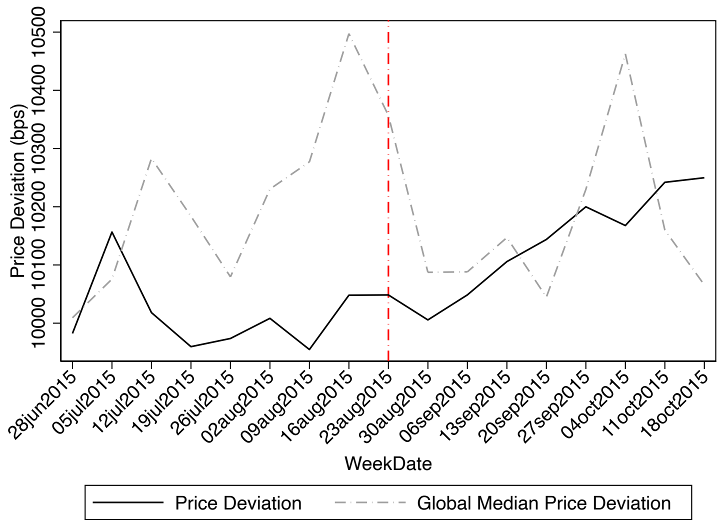
Panel A: Bitcoin price deviation



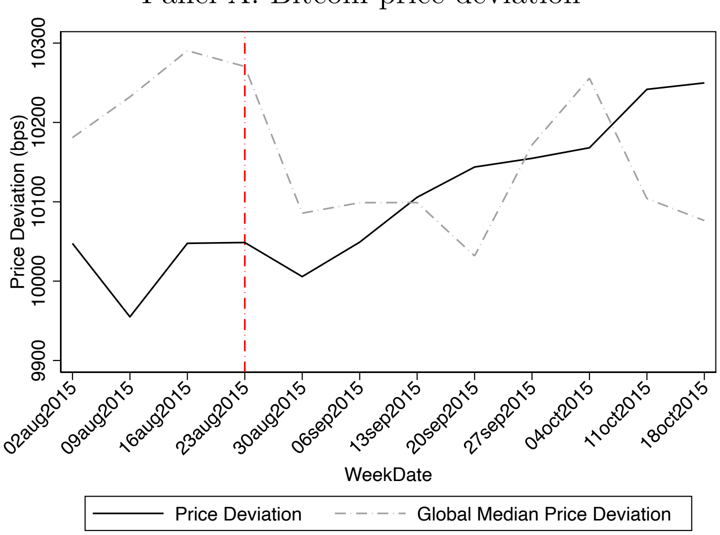
Panel B: Ethereum price deviation

Notes: The figure plots the Bitcoin and Ethereum price deviations around September 1, 2019, when the Argentina government imposed new capital controls to combat the Peso depreciation crisis. Panel A plots the Bitcoin price deviations from June 7 to October 27, 2019 (16 weeks around the event date). Panel B plots the Ethereum price deviations in the same time window.

Figure 2: The 2015 China stock market crash



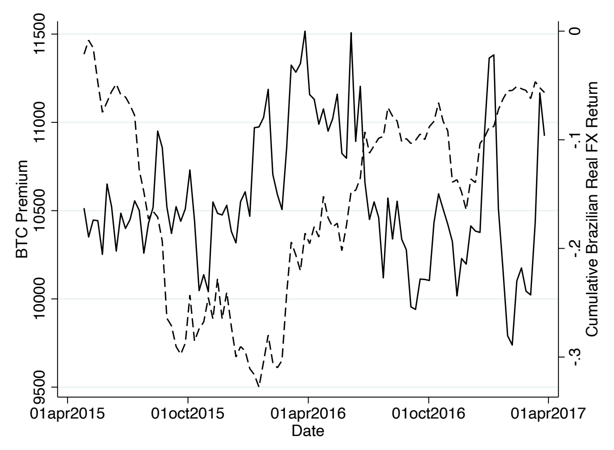
Panel A: Bitcoin price deviation



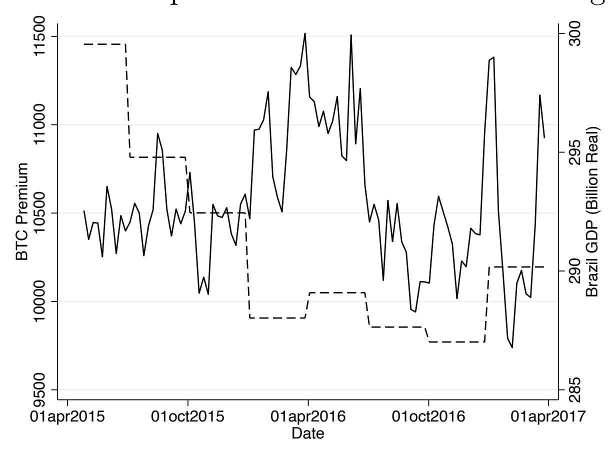
Panel B: Ethereum price deviation

Notes: The figure shows the Bitcoin and Ethereum price deviation around August 23, 2015, the biggest one-day loss in the Chinese stock market crash. Panel A plots the Bitcoin price deviations from June 28 to October 18, 2015 (16 weeks around the event date). Panel B plots the Ethereum price deviations from August 2 to October 18, 2015, as the Ethereum price data begin from August 2, 2015. There are only four-week price data before August 23, 2015.

Figure 3: Brazil's economic recession



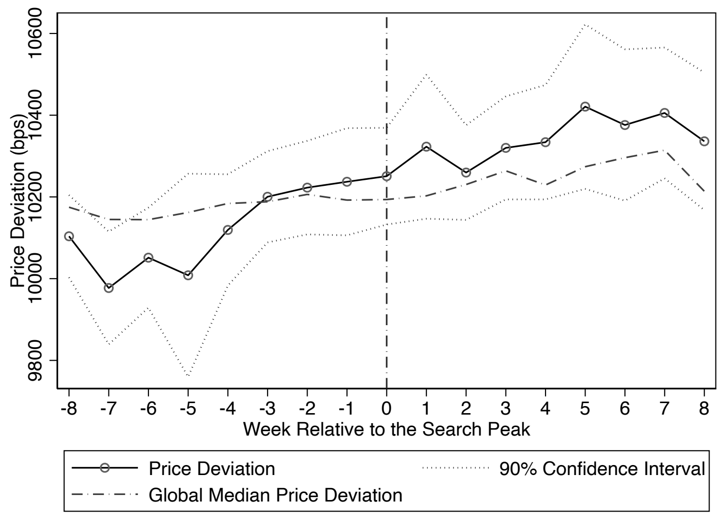
Panel A: Bitcoin price deviation and the exchange rate



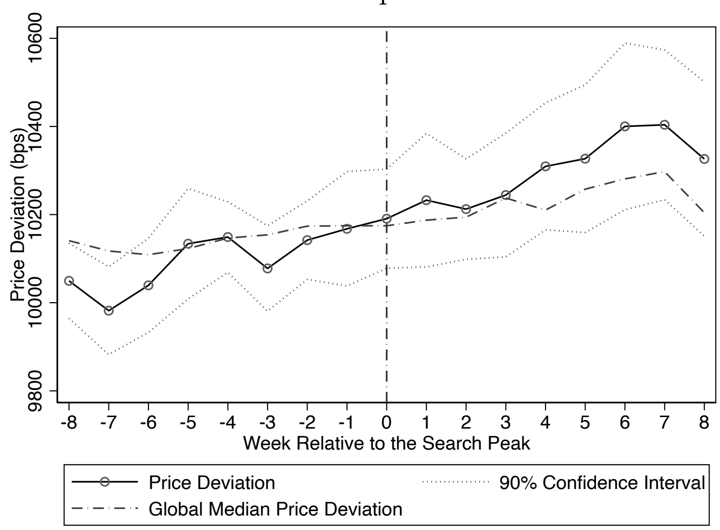
Panel B: Bitcoin price deviation and Brazilian GDP

Notes: This figure plots the time-series relationship between Bitcoin price deviations, the Brazilian Real exchange rate, and Brazil's GDP. In Panel A, the solid line is the BTC price deviation, and the dashed line is the normalized exchange rate. The exchange rate index was normalized to zero on April 1, 2015, and each point represents the cumulative currency returns since April 2015. In Panel B, the solid line is the BTC price deviation, and the dashed line represents Brazil's quarterly GDP in the current U.S. dollar.

Figure 4: Event studies: price deviations around political scandals



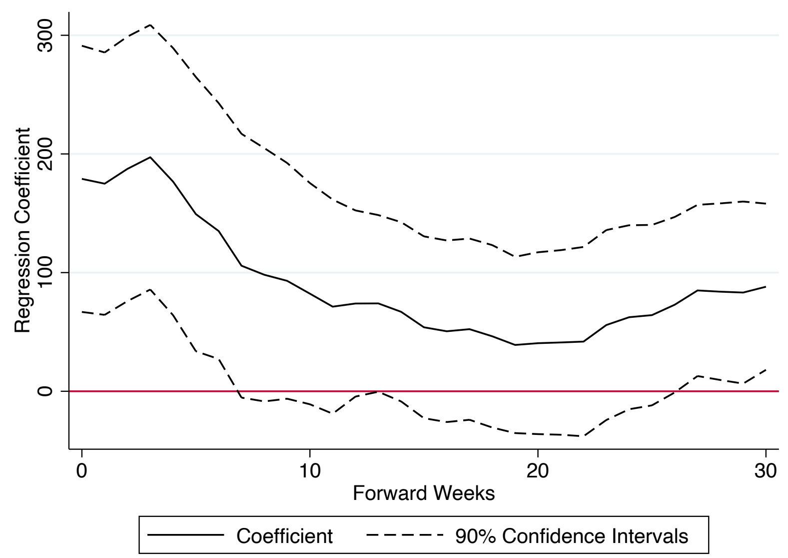
Panel A: Bitcoin price deviation



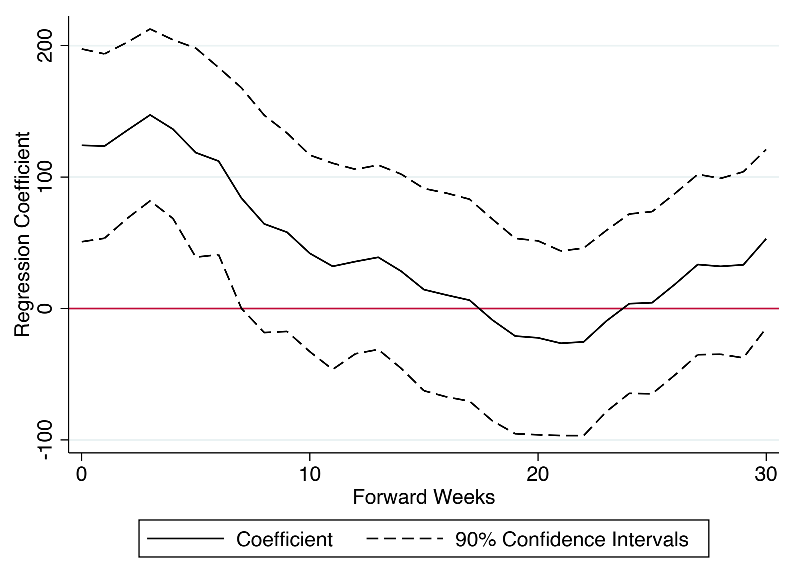
Panel B: Ethereum Price Deviation

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 43 political events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the average global median price deviations of the 31 countries in the same event window. Panel A plots the Bitcoin price deviations, and Panel B plots the Ethereum price deviations.

Figure 5: Dynamic price responses to the institutional failure attention



Panel A: Bitcoin dynamic price responses



Panel B: Ethereum dynamic price responses

Notes: This figure plots the dynamic responses β_k of cryptocurrency price deviations to the institutional failure attention index (IFA) by estimating the following panel regressions with price deviations in the next 30 weeks:

$$Deviation_{c,t+k} = \alpha + \beta_k IFA_{c,t} + \epsilon_{c,t}$$

The first data point β_0 is our baseline panel regression coefficient in Table 4, Column (1). Panel A plots the dynamic coefficients of Bitcoin price deviations, and Panel B plots the dynamic coefficients of Ethereum price deviations.

Table 1: Summary Statistics

Panel A summarizes cryptocurrency trading data: price deviation and trading volume. Panel B summarizes cryptocurrency and FX currency returns. Panel C summarizes variables related to Google Trends: the institutional failure attention index (IFA) and Google Trends indices for keywords "conflict," "crisis," "instability," "scandal," "bitcoin," and "ethereum". Panel D reports country features: trust scores, perceived corruption control, and confidence in various institutions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	S.D.	25^{th} Percentile	Median	75^{th} Percentile	Obs.
Panel A: Crypto Trading Data						
$Deviation\_BTC$	10312.16	1323.48	9975.70	10143.15	10511.62	7,688
$Deviation\_ETH$	10236.81	1390.78	9963.39	10130.68	10476.38	6,943
$LogVolume\_BTC$	5.61	3.06	3.44	5.06	7.77	7,688
$LogVolume\_ETH$	15.75	1.40	15.15	15.86	16.50	6,943
Panel B: Crypto and Currency Returns						
$Ret^{BTC}_{USD,t-9\to t-1}$	0.18	0.41	-0.082	0.079	0.36	7,688
$Ret^{ETH}_{USD,t-9\to t-1}$	0.53	1.50	-0.22	0.062	0.49	6,917
$Ret^{Currency}_{c,t-9\to t-1}$	1.00	0.038	0.98	1.00	1.01	7,688
Panel C: Google Search Data						
IFA	-0.1	0.97	-0.82	-0.21	0.55	7,688
$GT\_Conflict$	181.34	65.46	126.53	181.23	227.12	7,688
GT_Crisis	143.94	61.51	100.88	140.10	184.19	7,688
$GT\_Instability$	124.19	63.67	76.50	113.53	166.21	7,688
$GT\_Scandal$	165.65	55.14	128.92	162.33	201.42	7,688
$GT\_Bitcoin$	13.16	14.78	4	9	16	7,688
$GT\_Ethereum$	14.78	17.24	4	9	18	6,943
GT_Gold	61.96	15.41	52	63	73	7,688
$\Delta GT\_Bitcoin$	1.05	0.38	0.83	0.99	1.18	7,688
$\Delta GT\_Ethereum$	1.10	0.79	0.73	0.95	1.27	6,943
Panel D: Country Feature						
Trust (GPS)	0.0327	0.293	-0.167	-0.00269	0.299	31
Most People Trusted (WVS)	25.58	15.67	12.2	23.1	33.3	28
Corruption in Business	-5	38.1	-31.9	-11	24.3	17
Corruption in State	-12.11	56.92	-55.9	-33.2	37.4	17
Confidence in Bank	12.92	62.51	-46.95	-1.2	77.8	20
Confidence in Companies	-14.2	36.61	-46.1	-27.6	10.7	27
Confidence in Government	-14.94	68.65	-65.5	-22.5	20.4	27

Table 2: Event studies on the price deviation

This table reports the pre and post changes in price deviation for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unidentified Google Trends spikes in Column (5). In Panel A, the dependent variable is the Bitcoin price deviation. In Panel B, the dependent variable is the Bitcoin price deviation minus the global market median deviation. In Panel C, the dependent variable is the Ethereum price deviation. In Panel D, the dependent variable is the Ethereum price deviation minus the global market median deviation. The event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
	Panel A: Dependent Variable $Deviation_{BTC}$				
Post	199.858***	216.371**	-141.209	11.329	91.466
	(56.452)	(70.311)	(105.190)	(66.035)	(105.084)
	Panel B: Dependent Variable $Adjusted\_Deviation_{BTC}$				
Post	137.054***	102.347	-146.197	-14.081	-7.897
	(41.429)	(65.735)	(92.326)	(62.878)	(103.693)
# events	43	5	6	17	17
	Panel C: Dependent Variable $Deviation_{ETH}$				
Post	177.571***	236.393*	17.407	8.088	24.591
	(50.961)	(85.508)	(25.353)	(61.554)	(79.483)
	Panel D: Dependent Variable $Adjusted\_Deviation_{ETH}$				
Post	101.353***	90.353	-136.385	-11.021	-77.599
	(33.028)	(91.411)	(159.152)	(66.918)	(69.006)
# events	41	4	4	15	17

Table 3: Price deviation responses to the institutional failure attention

This table reports panel regressions of the cryptocurrency price deviation on the institutional failure attention index (IFA) in Columns (1), (6) and cumulative Google Trends for "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5) by estimating the following regressions:

$$Deviation_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the IFA and cumulative Google Trends indices. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panels A and B and the Ethereum price deviation in Panels C and D. In Column (6), the countries with tight capital control are excluded from the sample. The country fixed effects are included in Panels A and C, whereas both country and week fixed effects are included in Panels B and D. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$					
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal	(6) IFA
Google Trends	179.002**	149.784**	67.093**	125.198**	87.498**	133.813**
	(68.183)	(64.665)	(32.260)	(60.412)	(39.698)	(54.843)
Currency FE	YES	YES	YES	YES	YES	YES
	Panel B: Dependent Variable $Deviation_{BTC}$					
Google Trends	121.753*	78.878	-5.515	130.485*	9.141	69.951
	(67.161)	(50.604)	(23.143)	(66.676)	(37.858)	(64.153)
Currency FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
# observation	7,688	7,688	7,688	7,688	7,688	6,200
	Panel C: Dependent Variable $Deviation_{ETH}$					
Google Trends	121.147***	91.077**	33.990	120.156*	-19.781	105.188**
	(43.121)	(43.503)	(27.420)	(68.427)	(60.913)	(44.719)
Currency FE	YES	YES	YES	YES	YES	YES
	Panel D: Dependent Variable $Deviation_{BTC}$					
Google Trends	175.050**	139.654*	13.000	150.535*	-31.088	173.288*
	(80.512)	(77.810)	(32.108)	(79.753)	(63.202)	(100.159)
Currency FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
# observation	6,943	6,943	6,943	6,943	6,943	5,598

Table 4: Price deviation responses with country features

This table reports regressions that horse-race IFA with other country features $Feature_{c,t}$: GDP per capita growth in Column (2), credit by the private sector in Column (3), annual inflation in Column (4), the WGI rule of law index in Column (5), WGI government effectiveness index in Column (6), and WGI corruption control score in Column (7).

$$Deviation_{c,t} = \beta_1 IFA_{c,t} + \beta_2 Feature_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $IFA_{c,t}$ denotes the institutional failure index. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panels A and B and the Ethereum price deviation in Panels C and D. The country fixed effects are included in Panels A and C, whereas both country and week fixed effects are included in Panels B and D. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) N/A	(2) GDP Growth	(3) Credit	(4) Inflation	(5) Law	(6) Gov Eff	(7) Corruption
	Panel A: Dependent Variable $Deviation_{BTC}$						
IFA	179.002**	195.844**	161.081**	113.700**	176.445***	182.111**	167.740***
	(68.183)	(76.134)	(63.596)	(47.518)	(61.746)	(68.268)	(57.404)
Feature		6.530	-5.140	22.361***	-1168.374	-192.691	-1281.128
		(5.415)	(11.035)	(5.816)	(1007.516)	(498.590)	(897.063)
Currency FE	YES	YES	YES	YES	YES	YES	YES
	Panel B: Dependent Variable $Deviation_{BTC}$						
IFA	121.753*	123.113*	111.884	60.271	108.481*	120.721*	102.432*
	(66.068)	(67.091)	(68.285)	(48.238)	(58.544)	(64.491)	(58.997)
Feature		11.119	-1.641	21.714***	-1221.885	-177.432	-1255.144
		(10.353)	(9.561)	(5.650)	(975.709)	(535.380)	(798.952)
Week FE	YES	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES	YES
# observation	7,688	7,688	7,030	7,440	7,440	7,440	7,440
	Panel C: Dependent Variable $Deviation_{ETH}$						
IFA	121.147***	133.478***	125.229***	94.104**	121.927***	123.972***	120.537***
	(43.121)	(45.696)	(44.966)	(39.721)	(41.478)	(43.533)	(41.737)
Feature		8.575**	13.495	29.087**	-831.800	46.686	-761.633
		(4.063)	(15.863)	(13.813)	(746.187)	(467.397)	(581.973)
Currency FE	YES	YES	YES	YES	YES	YES	YES
	Panel D: Dependent Variable $Deviation_{ETH}$						
IFA	175.050**	174.631**	180.092**	153.866*	170.768**	178.954**	172.486**
	(79.558)	(79.026)	(80.805)	(81.076)	(82.184)	(80.423)	(80.053)
Feature		4.559	17.267	28.058**	-728.744	134.451	-621.567
		(6.496)	(15.612)	(11.167)	(830.564)	(493.913)	(590.321)
Week FE	YES	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES	YES
N	6,943	6,943	6,332	6,717	6,717	6,717	6,717

Table 5: Institutional failures and attention to cryptocurrency

This table reports the impact of institutional failures on attention to cryptocurrencies. In Panel A, the dependent variable is the growth of "bitcoin" Google Trends index $\Delta GT\_Bitcoin_t = \frac{8 \times GT\_Bitcoin_t}{\sum_{i=1}^{i=8} GT\_Bitcoin_{t-i}}$. In Panel B, the dependent variable is the growth in "Ethereum" Google searches $\Delta GT\_Ethereum_t = \frac{8 \times GT\_Ethereum_t}{\sum_{i=1}^{i=8} GT\_Ethereum_{t-i}}$. The independent variable is the institutional failure attention index (IFA) in Column (1) and cumulative Google Trends for "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5).

$$\Delta GT\_Crypto_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the IFA and cumulative Google Trends indices. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $\Delta GT\_Bitcoin$				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	0.077***	0.065***	0.062***	0.035**	0.017
	(0.023)	(3.064)	(3.045)	(2.089)	(1.211)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $\Delta GT\_Ethereum$				
Google Trends	0.173***	0.165***	0.113***	0.064	0.084***
	(0.044)	(0.042)	(0.033)	(0.045)	(0.025)
# observation	6,943	6,943	6,943	6,943	6,943

Table 6: Heterogeneous price responses by trust

This table reports the heterogeneous price response to the institutional failure attention (IFA) index by the country's trust level from Global Preference Survey (GPS). High-trust countries in Column (2) refer to 11 countries with GPS trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a GPS trust score between -0.1 and 0.2. In Column (4), low-trust countries refer to 11 countries with a GPS trust score below -0.1. Column (5) reports the test for heterogeneous response by trust level:

$$Deviation_{c,t} = \beta_1 IFA_{c,t} + \beta_2 Distrust_c \times IFA_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $IFA_{c,t}$ denotes the IFA index. $Distrust_c$ is GPS trust score. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1)	(2)	(3)	(4)	(5)
	Full	High-trust	Mid-trust	Low-trust	Full
IFA	179.002**	31.016	242.712	304.812*	-226.601
	(68.183)	(35.819)	(132.321)	(160.795)	(164.464)
$IFA \times Distrust$					427.311**
					(201.943)
# obsercation	7,688	2,728	2,232	2,728	7,688
	PanelB: Dependent Variable $Deviation_{ETH}$				
IFA	121.147***	3.961	203.424**	196.654**	-93.644
	(43.121)	(35.889)	(77.517)	(73.709)	(126.619)
$IFA \times Distrust$					228.488*
					(126.705)
# obsercation	6,943	2,465	1,999	2,479	6,943

Table 7: Horse-racing regressions with other country features

This table reports regressions that horse-race trust with other country features $Feature_{c,t}$: GDP per capita in Column (2), credit by the private sector in Column (3), annual inflation in Column (4), the WGI rule of law index in Column (5), WGI government effectiveness index in Column (6), and WGI corruption control score in Column (7).

$$Deviation_{c,t} = \beta_1 IFA_{c,t} + \beta_2 Distrust_c \times IFA_{c,t} + \beta_3 Feature_{c,t} \times IFA_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $IFA_{c,t}$ denotes the institutional failure attention index. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$						
	(1) N/A	(2) GDP	(3) Credit	(4) Inflation	(5) Law	(6) Gov Eff	(7) Corruption
IFA	-226.601	-511.609	-235.615	-117.784	-277.127	-266.213	-71.256
	(164.464)	(899.795)	(161.775)	(115.679)	(188.057)	(174.342)	(200.686)
$IFA \times Distrust$	427.311**	436.314*	445.419**	259.570**	471.686**	469.739**	340.061**
	(201.943)	(215.008)	(194.979)	(118.427)	(215.214)	(211.149)	(165.781)
$IFA \times Covariate$		10.187	-4.742	1.108	25.141	17.243	-1.160
		(28.888)	(67.908)	(9.117)	(76.637)	(53.407)	(1.423)
# observation	7,688	7,688	7,030	7,441	7,440	7,440	7,440
	Panel B: Dependent Variable $Deviation_{ETH}$						
IFA	-93.644	513.813	-38.285	-54.973	-25.212	-39.064	68.699
	(126.619)	(982.595)	(140.696)	(119.901)	(152.640)	(145.065)	(209.727)
$IFA \times Distrust$	228.488*	213.656	199.152	199.264	195.649	192.075	150.548
	(126.705)	(139.900)	(127.972)	(117.475)	(134.705)	(135.054)	(155.222)
$IFA \times Covariate$		-21.883	-50.744	-8.997	-55.547	-45.759	-0.999
		(32.521)	(38.785)	(15.800)	(46.471)	(33.779)	(0.871)
# observation	6,943	6,943	6,332	6,718	6,717	6,717	6,717

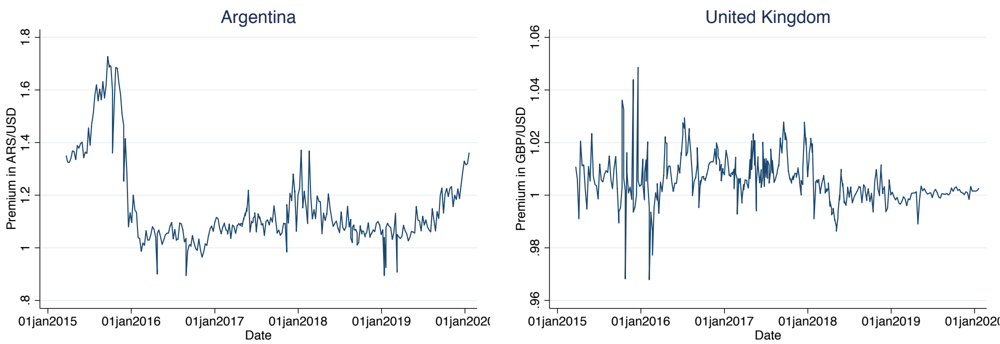
Table 8: Capital controls and price deviation responses

This table reports how capital controls (measured with the annually updated Ito-Chinn capital account openness index) interact with cryptocurrency price responses to the institutional failure attention (IFA) index. The dependent variable is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. Column (1) reports the uni-variate regressions of the price deviation response to the IFA. Column (3) reports the uni-variate regressions of the price deviation response on the capital account closeness index (one minus the Ito-Chinn capital account openness index). Column (5) reports regressions that include both IFA and capital account closeness. Column (7) reports regressions that add an interaction term of IFA and capital account closeness in addition to the specification in Column (5). We further report regressions that control the year fixed effects in Columns (2), (4), (6), and (8). The country fixed effects are included in all specifications. Robust standard errors are clustered at the currency and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IFA	179.002**	139.890**			155.886***	125.439**	143.718**	113.813**
	(68.183)	(54.702)			(54.726)	(45.922)	(53.222)	(45.878)
$Closeness$			669.315***	653.387***	616.567***	630.877***	626.578***	643.147***
			(6.219)	(54.666)	(5.899)	(45.771)	(25.119)	(59.294)
$IFA \times Closeness$							62.745	65.675
							(73.279)	(65.713)
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
# observation	7,688	7,688	7,688	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$							
IFA	121.147***	156.080**			116.136***	152.928**	102.136***	138.176**
	(43.121)	(65.812)			(41.457)	(65.194)	(35.613)	(57.018)
$Closeness$			282.464***	337.518***	260.210***	324.475***	288.555***	356.870***
			(42.041)	(36.179)	(54.863)	(36.836)	(45.977)	(38.335)
$IFA \times Closeness$							86.751*	94.491**
							(43.396)	(45.572)
Year FE	NO	YES	NO	YES	NO	YES	NO	YES
# observation	6,943	6,943	6,943	6,943	6,943	6,943	6,943	6,943

A Internet Appendix: Figures and Tables

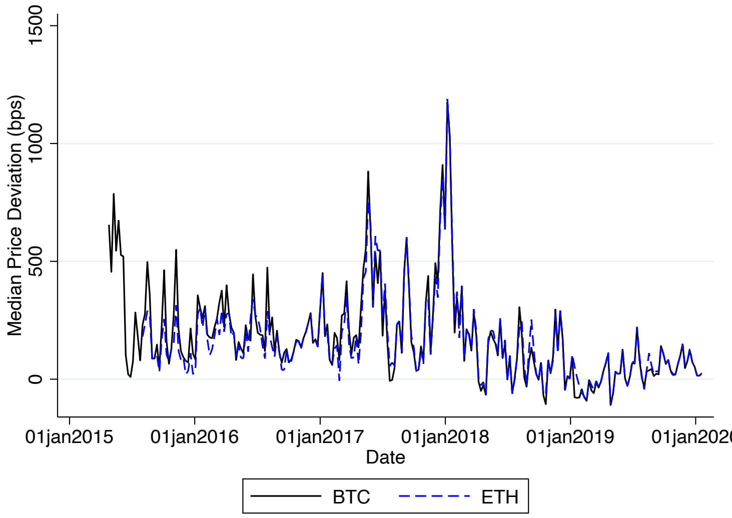
Figure A.1: The price deviations in Argentina and the United Kingdom



Notes: This figure plots the price deviations in Argentina and the United Kingdom from January 2015 to January 2022. The price deviation in the country c is defined as:

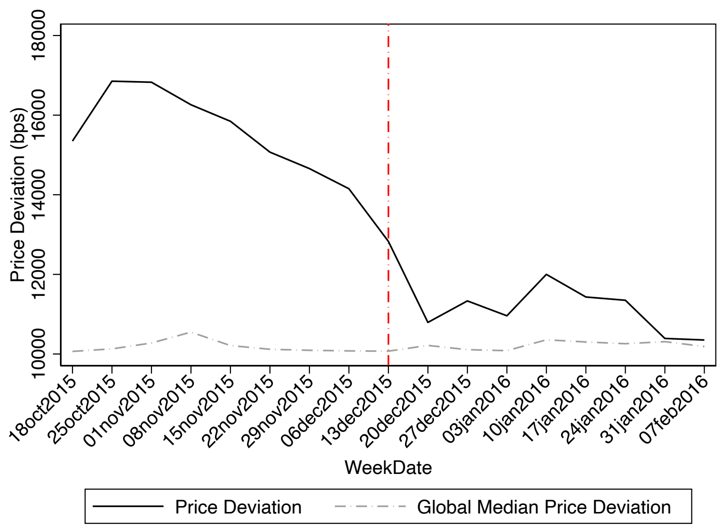
$$Deviation_{c,t} = \frac{Prc_{c,t} \times Exchange_{c-USD,t}}{Prc_{USD,t}}$$

Figure A.2: The median price deviation of 31 countries over time

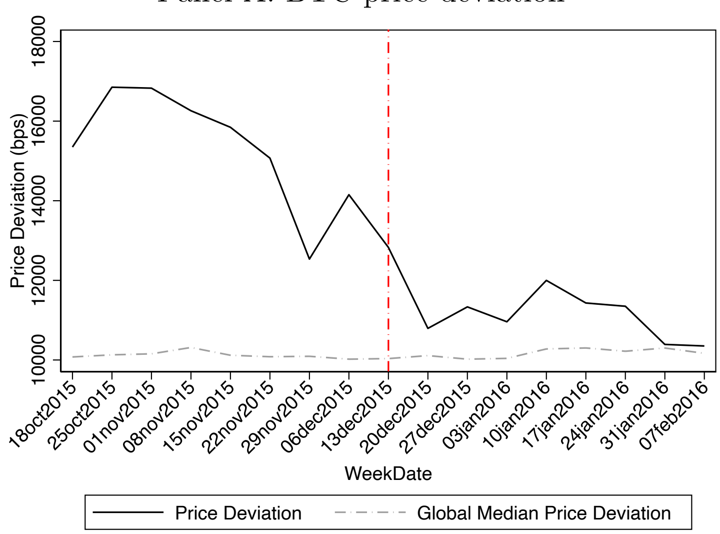


Notes: This figure plots the trend of the median number of price deviations of cryptocurrencies.

Figure A.3: Removal of capital controls in Argentina



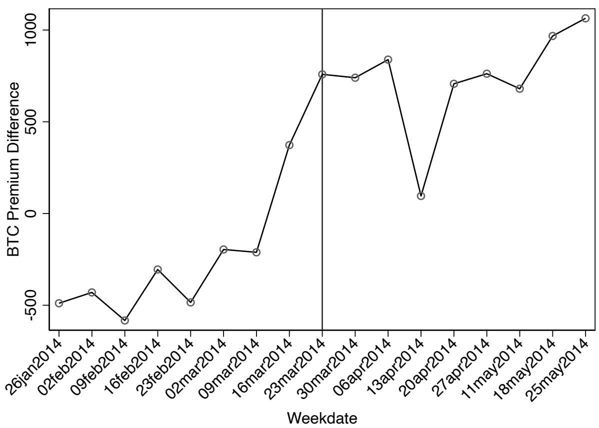
Panel A: BTC price deviation



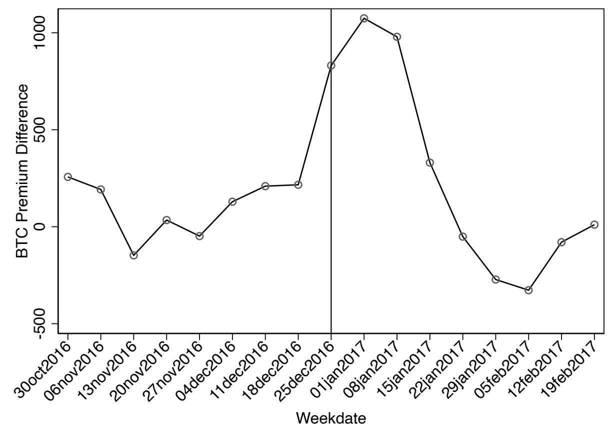
Panel B: ETH price deviation

Notes: The figure plots the Bitcoin and Ethereum price deviations around December 13, 2015, when the Argentina government removed capital controls to increase exports and spur economic growth. Panel A plots the Bitcoin price deviations from October 18, 2015, to February 7, 2016 (16 weeks around the event date). Panel B plots the Ethereum price deviations in the same time window.

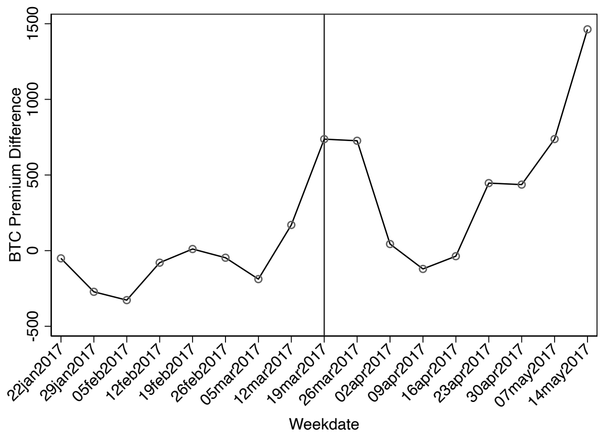
Figure A.4: Event studies: price deviations around three Brazilian political events



Panel A: Operation car wash



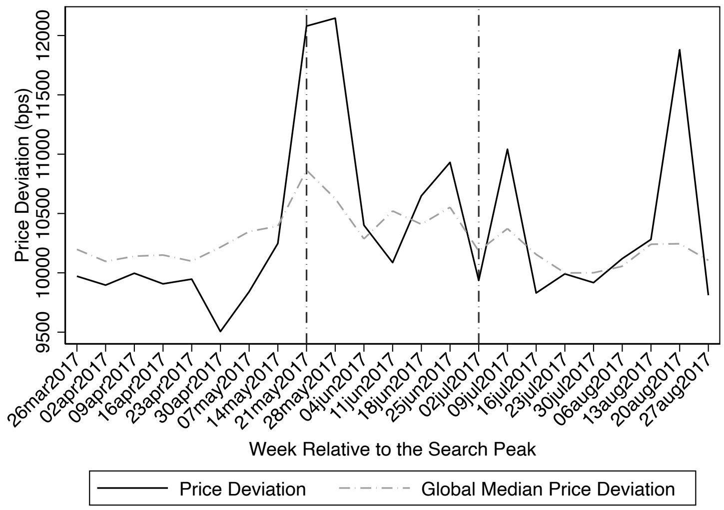
Panel B: Brazil's labor reform



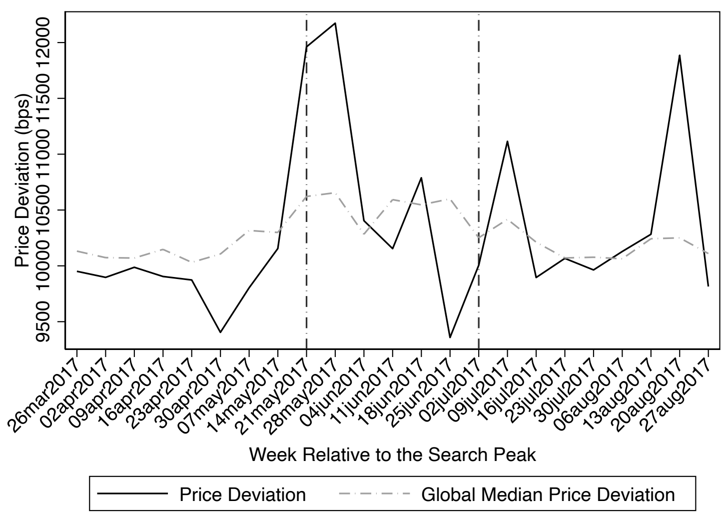
Panel C: Protests against the labor reform

Notes: The figure shows the Bitcoin price deviation around 16 weeks of the three events: Operation Car Wash known to the public on March 17, 2014, in Panel A; Brazil labor reform proposed on December 23, 2016, in Panel B; and protests against the labor reform erupted on March 15, 2017, in Panel C.

Figure A.5: Event studies: price deviations around Marawi conflict



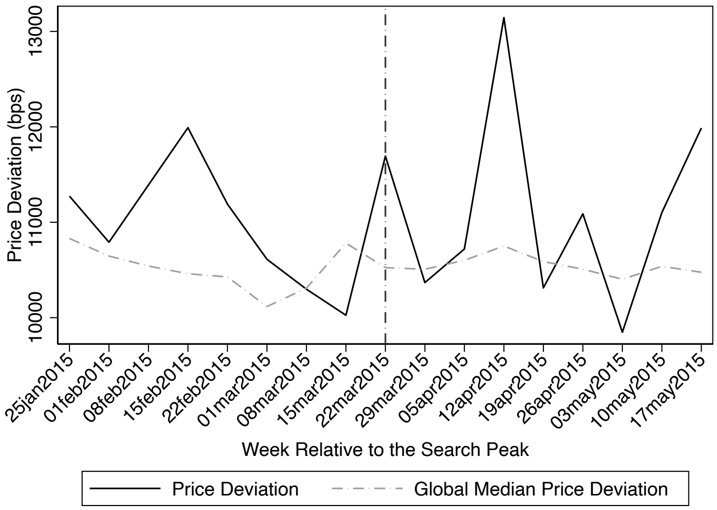
Panel A: BTC price deviation of Philippine



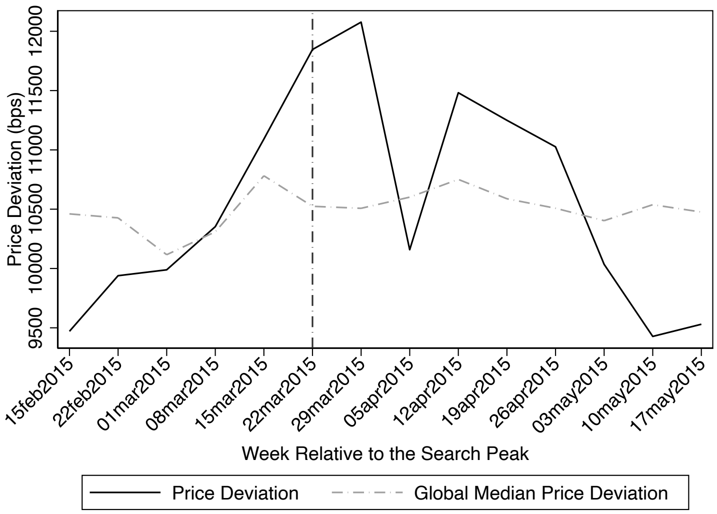
Panel B: ETH price deviation of Philippine

Notes: The figure shows the Bitcoin and Ethereum price deviation around the Marawi conflict in the Philippines. Panel A plots the trend of Bitcoin price deviation from March 26, 2017, to August 27, 2017 (16 weeks around the event date). Panel B plots the movement of Ethereum price deviation in the same time window.

Figure A.6: Event studies: price deviations around India-Pakistan conflict



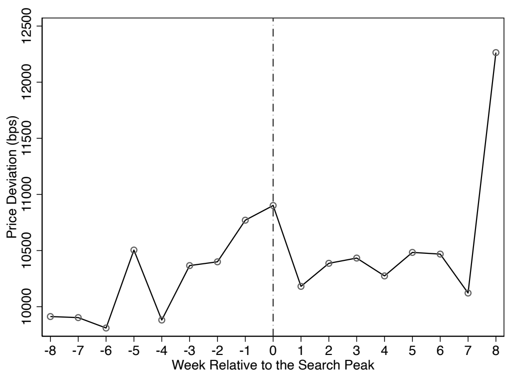
Panel A: BTC price deviation of India



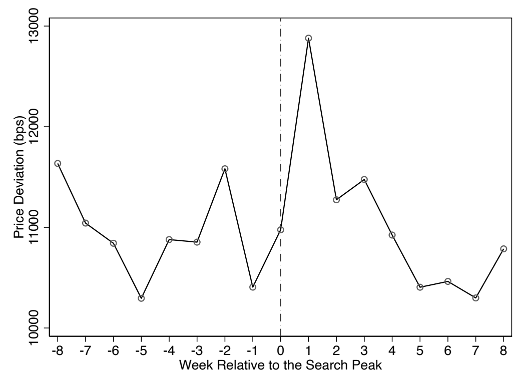
Panel B: BTC price deviation of Pakistan

Notes: The figure shows the Bitcoin and Ethereum price deviation around March 22, 2015, when the Indian-Pakistan conflict happened. Panel A plots the Bitcoin price deviations from January 25, 2015, to May 17, 2015 (16 weeks around the event date). Panel B plots the Ethereum price deviations from February 15, 2015, to May 17, 2015.

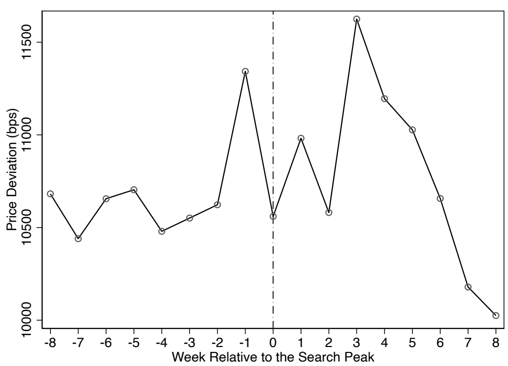
Figure A.7: Event studies: price deviations around events not inducing distrust



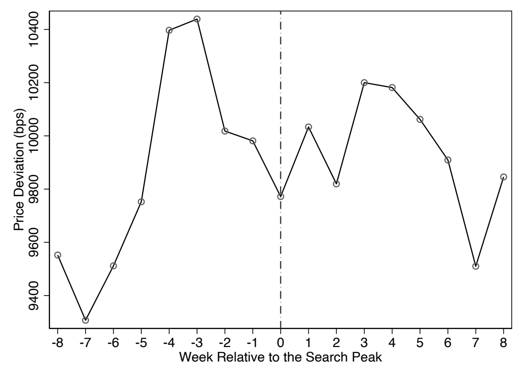
Panel A: Anti-corruption in Thailand



Panel B: Diplomatic conflict in Saudi Arabia



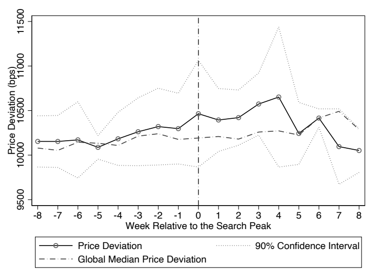
Panel C: Qatar diplomatic crisis in UAE



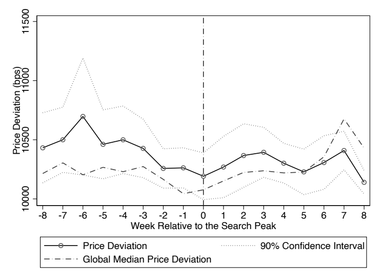
Panel D: Ceasefire deal in Colombia

Notes: This figure plots the Bitcoin price deviation around 16 weeks of 4 political scandals not inducing distrust: The anti-corruption in Thailand in Panel A, the diplomatic conflict of Saudi Arabia in Panel B, the Qatar diplomatic crisis in UAE in Panel C, and the ceasefire deal in Colombia in Panel D.

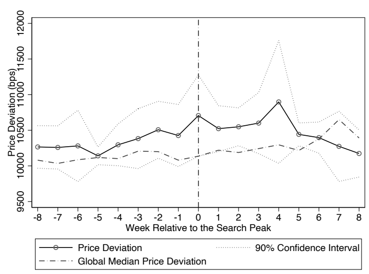
Figure A.8: Event study: price deviations around other socioeconomic events



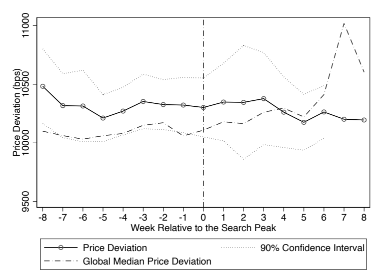
Panel A: Government-related socioeconomic Events (BTC)



Panel B: Government-unrelated socioeconomic events (BTC)



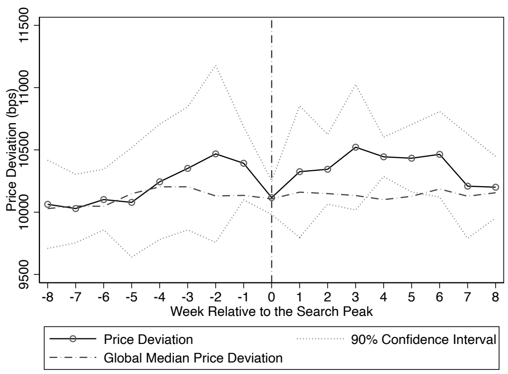
Panel C: Government-related socioeconomic Events (ETH)



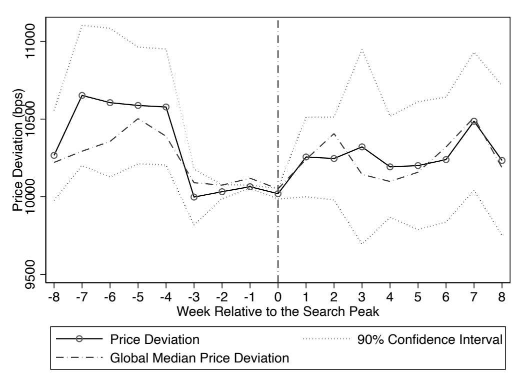
Panel D: Government-unrelated socioeconomic Events (ETH)

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 5 government-related and 6 government-unrelated socioeconomic events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries. Panels A and C show the Bitcoin and Ethereum price deviations of government-related socioeconomic events. Panels B and D show the Bitcoin and Ethereum price deviations of government-unrelated socioeconomic events.

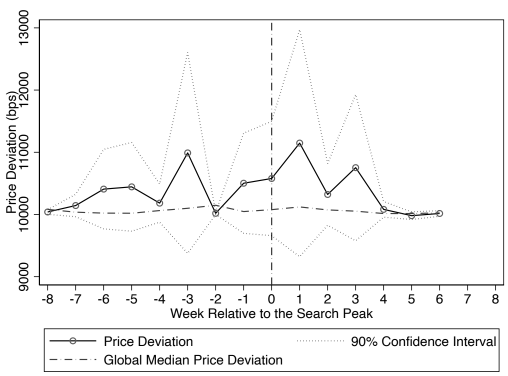
Figure A.9: Event study: price deviations around different types of irrelevant event



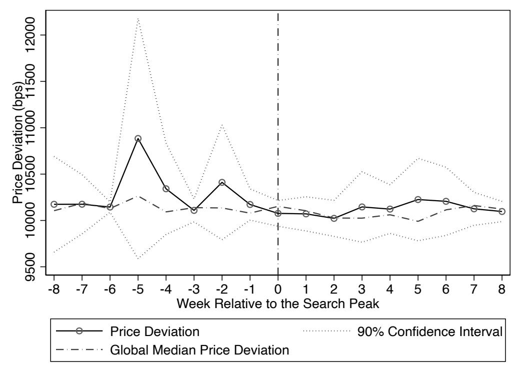
Panel A: Sex scandals



Panel B: Company scandals



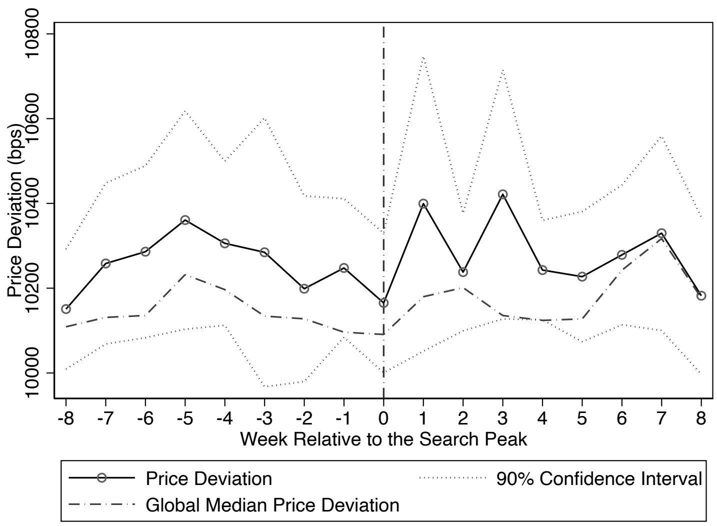
Panel C: Environmental crises



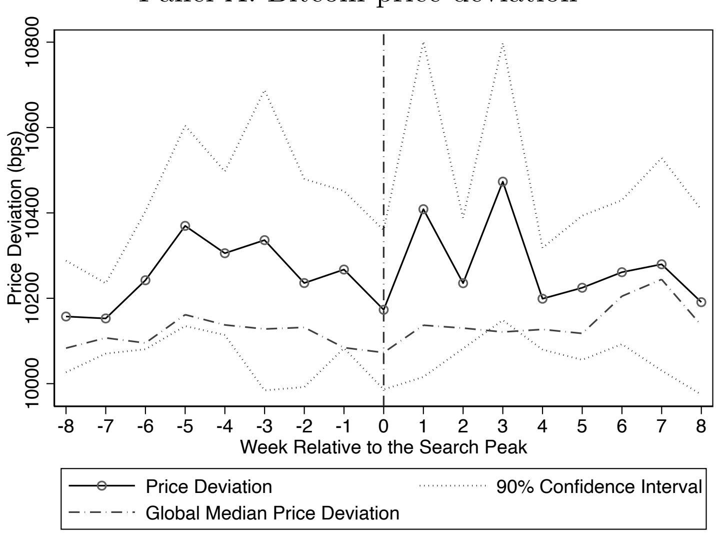
Panel D: Sports scandals

Notes: This figure plots the average Bitcoin price deviations in the 16-week time window around the event dates of four types of irrelevant events: sex scandals in Panel A, company scandals in Panel B, environmental crises in Panel C, and sports scandals in Panel D. As all three environmental crises happened in December 2019 and our data ends in January 2020, the event window is [-8,+6]. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries.

Figure A.10: Event study: price deviations around irrelevant events



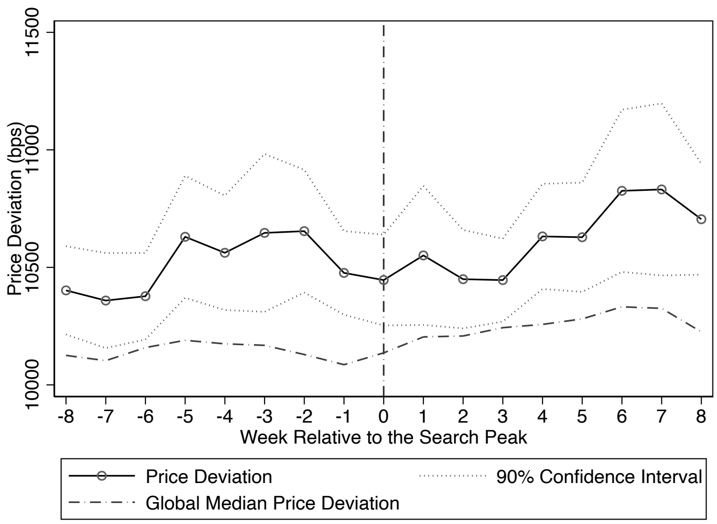
Panel A: Bitcoin price deviation



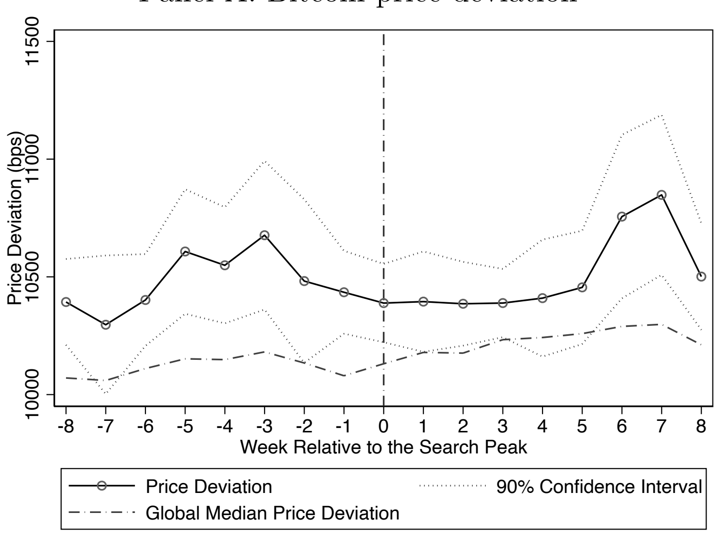
Panel B: Ethereum price deviation

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 17 irrelevant events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries. Panel A shows the Bitcoin price deviations, and Panel B shows the Ethereum price deviations.

Figure A.11: Event study: price deviations around unknown events



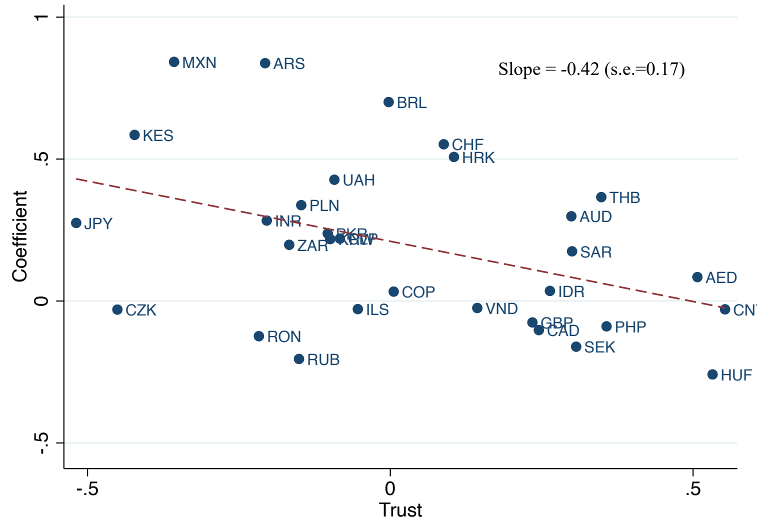
Panel A: Bitcoin price deviation



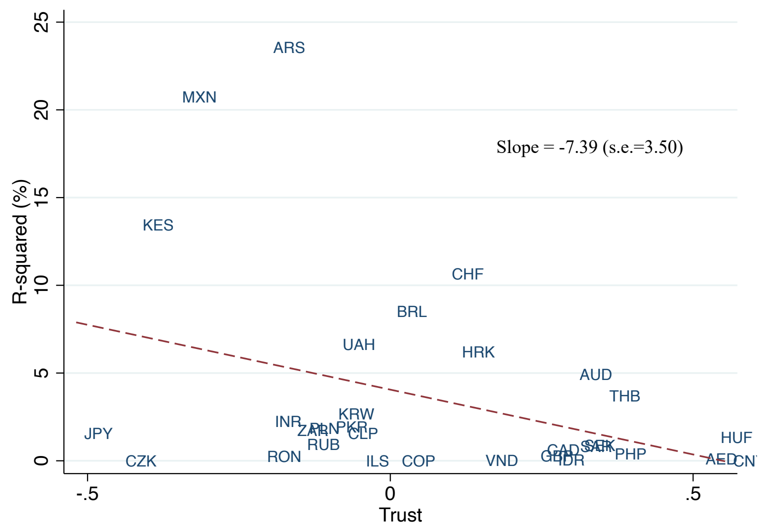
Panel B: Ethereum price deviation

Notes: This figure plots the average cryptocurrency price deviations in the 16-week time window around the event dates of 17 unknown events. The dotted lines represent the 90% confidence interval, and the dashed line indicates the global median price deviations of the 31 countries. Panel A shows the Bitcoin price deviations, and Panel B shows the Ethereum price deviations.

Figure A.12: Trust, R-squared, and standardized coefficients



Panel A: Coefficients by Country and Trust



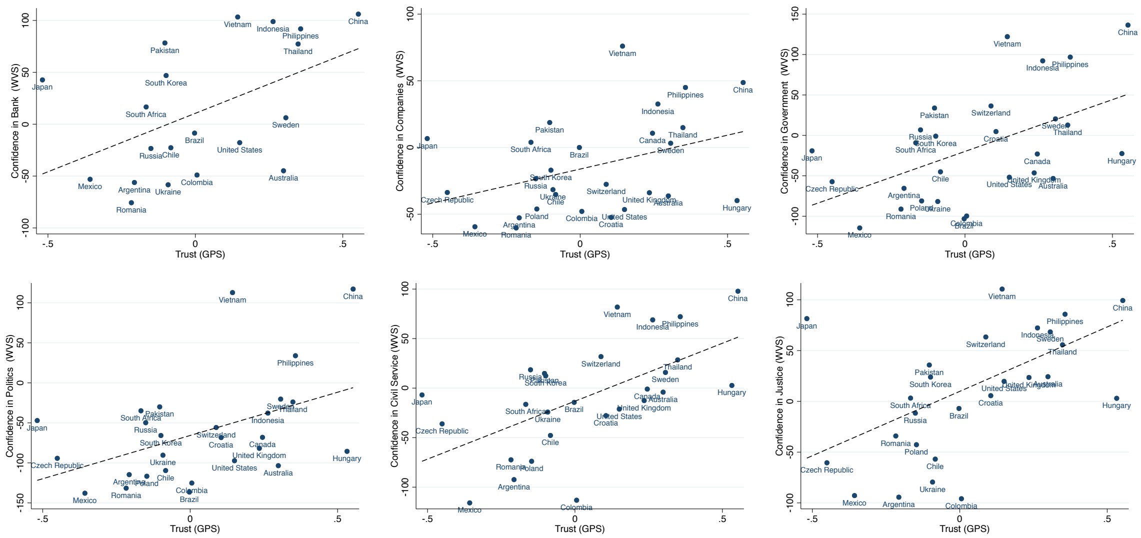
Panel B: R-squared by Country and Trust

Notes: This figure compares the explanatory power of our IFA index in the cryptocurrency price premium across the country. $\widehat{Deviation_{c,t}}$ is the normalized price deviation, which is scaled to mean zero and standard deviation of one for each country-cryptocurrency pair. We estimate the following time-series regression for each country, combining both Bitcoin and Ethereum data:

$$\widehat{Deviation_{c,t}} = \alpha_c + \beta_c IFA_{c,t} + \epsilon_{c,t}$$

Panel A correlates the trust level with β_c, and Panel B correlates the trust level with the R-squared obtained from the time-series regressions above.

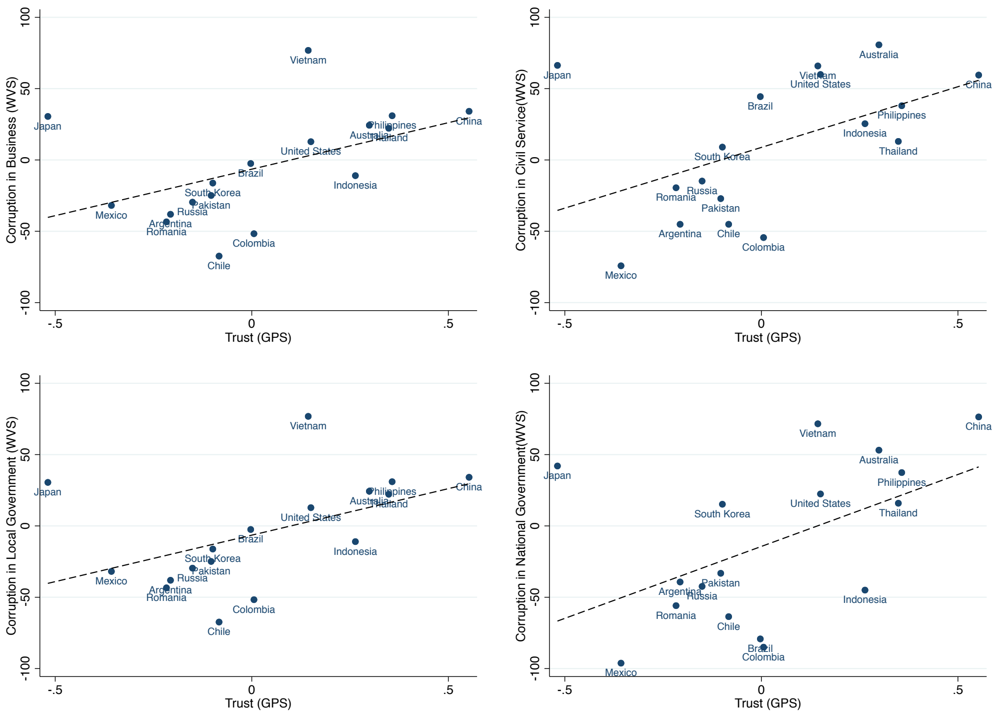
Figure A.13: Trust and confidence in institutions



Notes: This figure reports the relationship between trust and confidence scores in institutions, including banks, companies, government, politics, civil service, and justice. The trust measure is from the Global Preference Survey, and the confidence scores are computed from questions in the World Value Survey.

$$Confidence_c^{WVS} = Trust_c^{GPS} + \gamma\epsilon_c$$

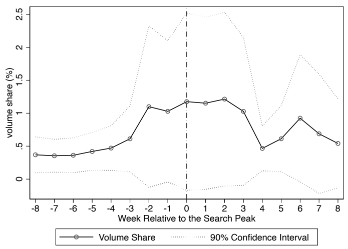
Figure A.14: Perceived corruption and trust



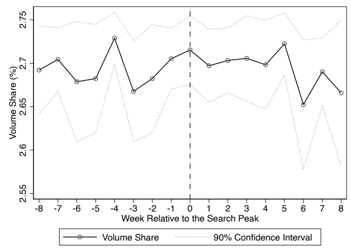
Notes: This figure plots the relationship between trust and perceived corruption in business, civil service, the local government, and the state/central government. The trust measure is from the Global Preference Survey, and the corruption control scores are computed from relevant questions from the World Value Survey.

$$Corruption_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

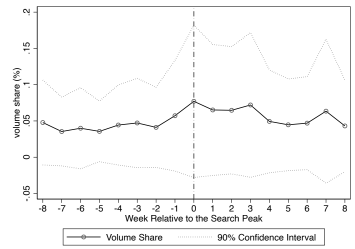
Figure A.15: Event studies: trading volume share around Google Trends peaks



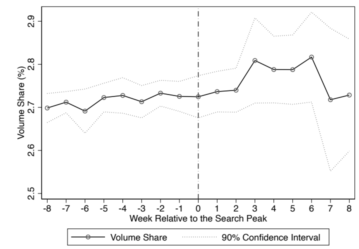
Panel A: Political scandals (BTC)



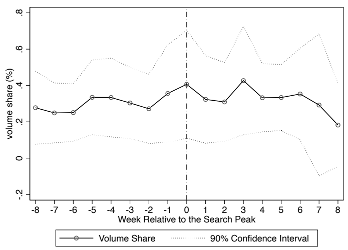
Panel B: Political scandals (ETH)



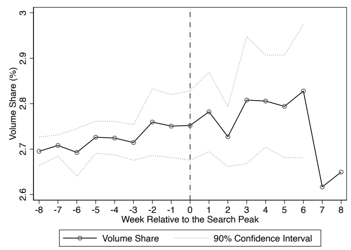
Panel C: Government-related socioeconomic events (BTC)



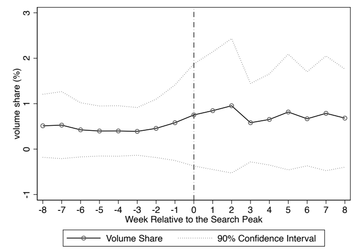
Panel D: Government-related socioeconomic events (ETH)



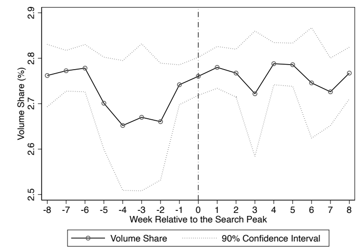
Panel E: Government-unrelated socioeconomic events (BTC)



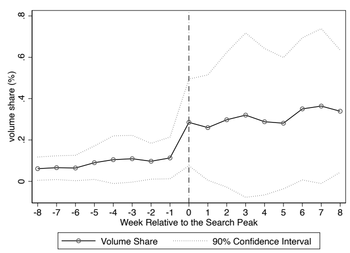
Panel F: Government-unrelated socioeconomic events (ETH)



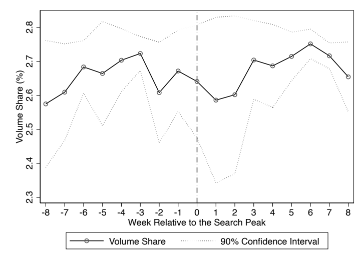
Panel G: Irrelevant events (BTC)



Panel H: Irrelevant events (ETH)



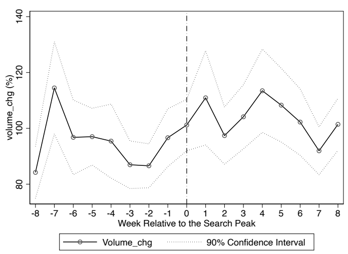
Panel I: Unknown events (BTC)



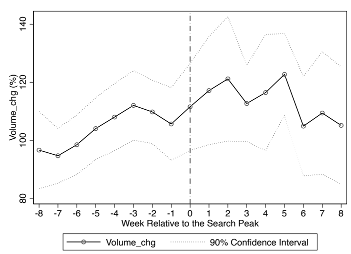
Panel J: Unknown events (ETH)

Notes: This figure reports the Bitcoin and Ethereum trading volume share in the 16-week time window around the event dates of political scandals, other socioeconomic events, irrelevant events, and unknown events. The trading volume share is the trading volume of country c divided by the total trading volume of 31 countries in week t. The dotted lines represent the 90% confidence interval.

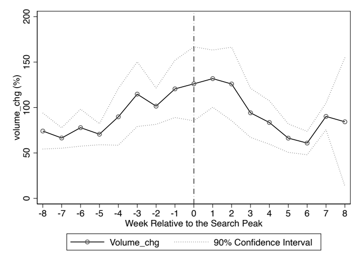
Figure A.16: Event studies: trading volume growth around Google Trends peaks



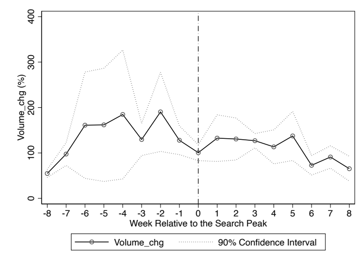
Panel A: Political scandals (BTC)



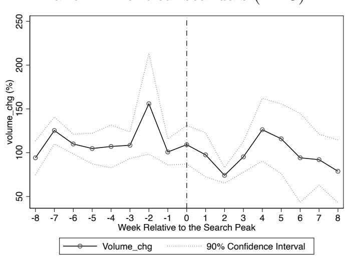
Panel B: Political scandals (ETH)



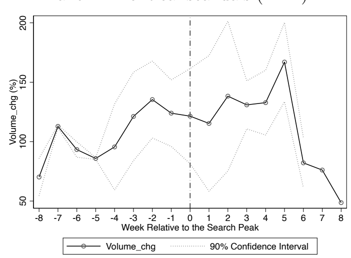
Panel C: Government-related socioeconomic events (BTC)



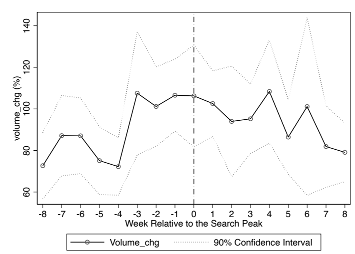
Panel D: Government-related socioeconomic events (ETH)



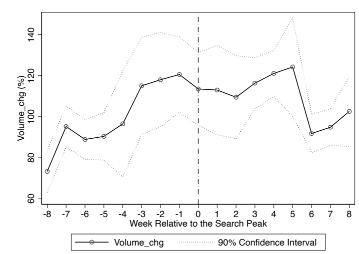
Panel E: Government-unrelated socioeconomic events (BTC)



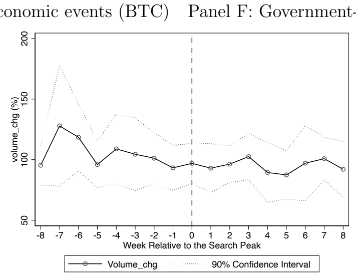
Panel F: Government-unrelated socioeconomic events (ETH)



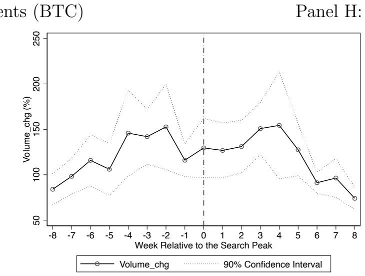
Panel G: Irrelevant events (BTC)



Panel H: Irrelevant events (ETH)



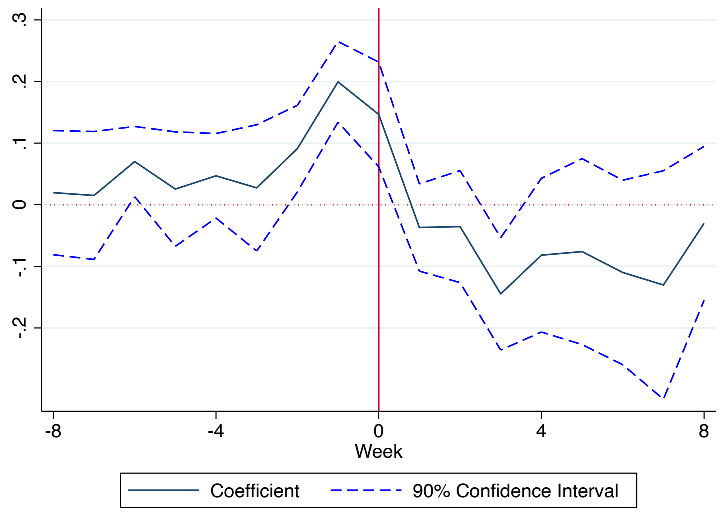
Panel I: Unknown events (BTC)



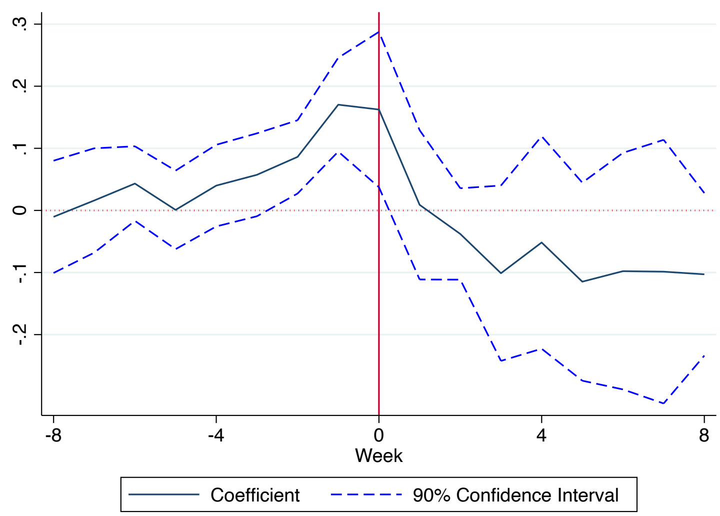
Panel J: Unknown events (ETH)

Notes: This figure reports the Bitcoin and Ethereum's trading volume growth$\Delta Volume_t = \frac{8 \times Volume_t}{\sum_{i=1}^{i=8} Volume_{t-i}}$ in the 16-week time window around the event dates of political scandals, other socioeconomic events, irrelevant events, and unknown events. The dotted lines represent the 90% confidence interval.

Figure A.17: Exchange rate and price deviation



Panel A: Bitcoin price deviation

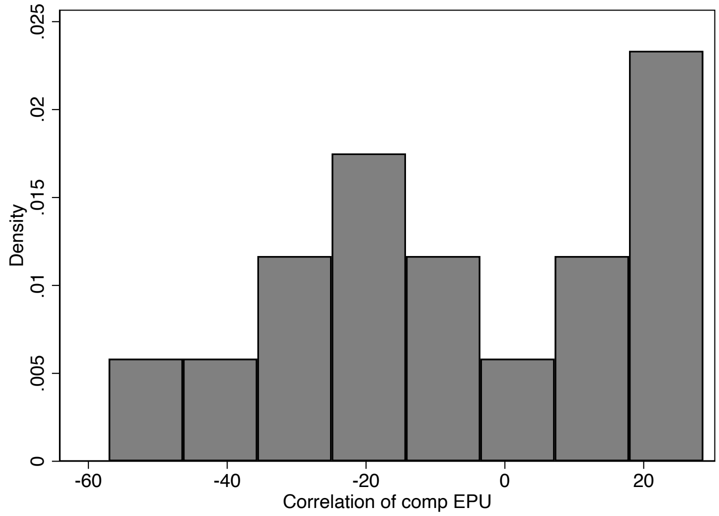


Panel B: Ethereum price deviation

Notes: This figure plots coefficients $\beta_{c,t}$ in uni-variate regressions of price deviations on lead-lag exchange rate returns from week -8 to week +8 ($i \in [-8, 8]$ in the following regression):

$$Deviation_{c,t} = \beta_{c,t+i} Ret_{c,t+i}^{Currency} + \gamma_c + \epsilon_{c,t}$$

Figure A.18: Correlation of IFA and EPU



Notes: This figure plots coefficients $\beta_{c,t}$ in uni-variate regressions of price deviations on lead-lag exchange rate returns from week -8 to week +8 ($i \in [-8, 8]$ in the following regression):

$$Deviation_{c,t} = \beta_{c,t+i} Ret^{Currency}_{c,t+i} + \gamma_c + \epsilon_{c,t}$$

Table A.1: Event study on Brazil economic slowdown

This table reports the regression results for the relationship between cryptocurrency price deviation and the cumulative return of the Brazilian Real from April 26, 2014, to March 2, 2017. The dependent variable is the price deviation in Columns (1), (3), and (4), and is the adjusted price deviation (the raw price deviation minus its global median) in Column (2). We control the weekly return of the Brazilian Real in Column (3) and the GDP of Brazil in Column (4). In Panel A, the dependent variable is the Bitcoin price deviation. In Panel B, the dependent variable is the Ethereum price deviation. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$			
	(1)	(2)	(3)	(4)
Curindex	-1079.866**	-1396.267***	-1160.968***	-1172.267***
	(427.270)	(397.033)	(419.938)	(437.304)
Logretcur			3964.104**	
			(1734.322)	
GDP				-11.212
				(10.075)
# Observation	101	101	101	101
	Panel B: Dependent Variable $Deviation_{ETH}$			
Curindex	-1107.358**	-1214.745***	-1283.889**	-1442.359**
	(514.423)	(456.445)	(511.480)	(560.872)
Logretcur			4274.506**	
			(2041.754)	
GDP				-28.589
				(19.710)
# Observation	87	87	87	87

Table A.2: Robustness event study: political events

This table reports the results of the event study by whether political events induce distrust: all events in Column (1), political scandals inducing distrust in Column (2), and political events not generating distrust toward government in Column (3). The dependent variable is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$		
	(1)	(2)	(3)
Post	199.858***	203.493***	165.391
	(56.452)	(61.918)	(88.076)
# events	43	39	4
	Panel B: Dependent Variable $Deviation_{ETH}$		
Post	177.571***	174.812***	211.402
	(50.961)	(54.718)	(102.037)
# events	41	38	3

Table A.3: Event studies on the price deviation based on euro crypto price

This table reports the pre and post changes in price deviation based on EUR crypto price for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unknown events (unidentified Google Trends spikes) in Column (5). In Panel A, the dependent variable is the Bitcoin price deviation. In Panel B, the dependent variable is the Bitcoin price deviation minus the global median deviation. In Panel C, the dependent variable is the Ethereum price deviation. In Panel D, the dependent variable is the Ethereum price deviation minus the global median deviation. The event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
Post	199.921***	217.413**	-202.281	16.297	84.691
	(55.783)	(61.507)	(134.684)	(67.375)	(98.278)
	Panel B: Dependent Variable $Adjusted\_Deviation_{BTC}$				
Post	135.531***	101.929	-147.119	-14.412	-8.765
	(41.643)	(65.722)	(92.043)	(63.130)	(103.541)
# events	43	5	6	17	17
	Panel C: Dependent Variable $Deviation_{ETH}$				
Post	152.517***	235.752*	11.571	13.107	28.475
	(48.601)	(81.235)	(25.678)	(60.218)	(79.117)
	Panel D: Dependent Variable $Adjusted\_Deviation_{ETH}$				
Post	91.021***	90.752	-135.847	-10.505	-77.501
	(32.198)	(91.187)	(158.574)	(66.833)	(68.945)
# events	41	4	4	15	17

Table A.4: Event studies on Google Trends index

This table reports the pre and post changes in attention to Bitcoin, Ethereum, and gold for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unidentified Google Trends spikes in Column (5). In Panel A, the dependent variable is the Google Trends index of "Bitcoin". In Panel B, the dependent variable is the Google Trends index of "Ethereum". In Panel C, the dependent variable is the Google Trends index of "gold". Event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable *GT_Bitcoin*				
	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
Post	5.395**	6.613	7.898	1.169	6.017
	(2.035)	(6.837)	(8.201)	(2.825)	(4.012)
# events	48	5	6	17	17
	Panel B: Dependent Variable *GT_ETH*				
Post	6.407**	11.308	15.335	2.528	7.897
	(2.610)	(10.387)	(13.722)	(3.658)	(4.731)
# events	46	4	4	15	17
	Panel C: Dependent Variable *GT_Gold*				
Post	1.189*	-0.850	6.977	0.487	0.333
	(0.681)	(2.319)	(4.416)	(2.339)	(1.620)
# events	48	5	6	17	17

Table A.5: Robustness: price deviation responses to institutional failures

This table reports robustness check for panel regressions of price deviation on the institutional failure attention index (IFA) as the principal component of the cumulative Google Trends index of "conflict," "crisis," "instability," and "scandal." The raw indices range from 0 to 100. The cumulative Google Trends index is defined as the eight-week discounted sum with a range of rate from 20% to 100%, where 20% is reported in Column(1), 40% is reported in Column(2), 60% is reported in Column(3), 80% is reported in Column(4), and 100% is reported in Column(5):

$$GT_{c,t} = \sum_{i=0}^{i=7} d^i \times Google_{c,t-i}$$

where $GT_{c,t}$ is the cumulative Google Trends index in country c, $Google_{c,t}$ denotes the raw weekly Google Trends index and d is the discount factor. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) 20%	(2) 40%	(3) 60%	(4) 80%	(5) 100%
IFA	95.141**	111.330**	139.910**	179.002**	203.568***
	(43.835)	(49.727)	(58.173)	(68.183)	(72.773)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$				
IFA	57.274*	67.803*	88.747**	121.147***	145.407***
	(30.522)	(33.936)	(38.453)	(43.121)	(44.982)
# observation	6,943	6,943	6,943	6,943	6,943

Table A.6: Correlation matrix of cumulative Google Trends indices

This table reports the correlation, mean, and standard deviation of the institutional failure attention index (IFA) and cumulative Google keyword search indices of four keywords: "conflict," "crisis," "instability," and "scandal". The raw indices range from 0 to 100. The cumulative Google Trends index is defined as the eight-week discounted sum with a rate of 80%:

$$GT_{c,t} = \sum_{i=0}^{i=7} 0.8^i \times Google_{c,t-i}$$

where $GT_{c,t}$ is the cumulative Google Trend index in country c, and $Google_{c,t}$ denote the raw weekly Google Trends index.

	IFA	Conflict	Crisis	Instability	Scandal
IFA	100%				
Conflict	87.99%	100%			
Crisis	26.10%	15.45%	100%		
Instability	78.85%	45.62%	-5.24%	100%	
Scandal	10.58%	13.55%	4.57%	-2.64%	100%
Mean	-0.094	181.34	143.93	124.19	165.65
S.D.	1.20	65.46	61.51	63.67	55.14

Table A.7: Price deviation responses with currency return control

This table reports the results of the effects of currency depreciation. We control the log cryptocurrency return in the past eight weeks in Column (2), the log return of local currency in Column (3), the cumulative log return of local currency in Column (4), and all three variables in Column (5). The independent variable is the Bitcoin price deviation in Panel A, and the Ethereum price deviation in Panel B. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$			
	(1)	(2)	(3)	(4)
IFA	179.002**	179.379**	160.523***	160.892***
	(68.183)	(68.119)	(55.241)	(55.209)
Logretcur		1501.522**		920.632
		(646.309)		(723.453)
Curindex			981.834***	974.551***
			(108.191)	(111.420)
# Observation	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$			
IFA	121.147***	121.115***	119.217***	119.277***
	(43.121)	(43.077)	(42.174)	(42.145)
Logretcur		1467.001		1335.180
		(921.021)		(916.928)
Curindex			242.067**	230.921**
			(107.302)	(104.146)
# Observation	6,943	6,943	6,943	6,943

Table A.8: Price deviation responses with cryptocurrency return control

This table reports the response of cryptocurrency price deviation to the institutional failure controlling for the past eight-week cryptocurrency returns. The independent variable is the institutional failure attention index (IFA) in Column (1) and cumulative Google keyword search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5). Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	172.874**	142.680**	59.109*	127.459**	88.098**
	(68.380)	(64.198)	(31.937)	(60.315)	(39.823)
$Ret^{BTC}_{USD,t-9\to t-1}$	165.345**	162.895**	170.826**	180.184***	178.882***
	(65.218)	(64.700)	(64.656)	(65.229)	(63.576)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$				
Google Trends	111.665**	83.314*	29.142	110.255	-27.351
	(46.232)	(45.195)	(27.323)	(70.532)	(60.579)
$Ret^{ETH}_{USD,t-9\to t-1}$	10.286	11.417	16.688	16.345	21.066
	(18.877)	(18.312)	(17.774)	(18.316)	(15.165)
# observation	6,917	6,917	6,917	6,917	6,917

Table A.9: Price deviation based on euro cryptocurrency price responses

This table reports panel regressions of the cryptocurrency price deviation calculated from euro crypto price on the institutional failure attention index (IFA) in Column (1) and cumulative Google Trends for "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5) by estimating the following regressions:

$$Deviation_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the IFA and cumulative Google Trends indices. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	176.562**	144.339**	63.365*	131.387**	84.237**
	(67.356)	(63.474)	(32.868)	(60.360)	(40.106)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $Deviation_{ETH}$				
Google Trends	125.101***	91.070**	33.288	129.982*	-20.118
	(42.813)	(42.703)	(27.715)	(68.558)	(61.023)
# observation	6,943	6,943	6,943	6,943	6,943

Table A.10: Cryptocurrency attention responses with crypto return control

This table reports the response of "Bitcoin" and "Ethereum" Google search growth to the institutional failure attention index (IFA) and four institutional failures ("conflict," "crisis," "instability," and "scandal") controlling for past eight-week cryptocurrencies returns. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $\Delta GT\_Bitcoin$				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	0.061***	0.047***	0.043***	0.040**	0.018
	(0.015)	(0.014)	(0.015)	(0.015)	(0.012)
$Ret^{BTC}_{USD,t-9\rightarrow t-1}$	0.423***	0.422***	0.422***	0.428***	0.427***
	(0.068)	(0.069)	(0.068)	(0.069)	(0.070)
# observation	7,688	7,688	7,688	7,688	7,688
	Panel B: Dependent Variable $\Delta GT\_Ethereum$				
Google Trends	0.106***	0.100***	0.072**	0.040	0.032
	(0.036)	(0.033)	(0.028)	(0.032)	(0.023)
$Ret^{ETH}_{USD,t-9\rightarrow t-1}$	0.137***	0.136***	0.141***	0.144***	0.142***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
# observation	6,917	6,917	6,917	6,917	6,917

Table A.11: Attention to "gold" and institutional failures

This table reports regressions of Google Trends index of "gold" on the institutional failure attention index (IFA) in Column (1) and the cumulative Google search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), and "scandal" in Column (5).

$$\Delta GT\_Gold_{c,t} = \beta GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the institutional failure attention index (IFA) and the cumulative Google Trends index of keywords related to institutional failures. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable ΔGT_Gold				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	-0.00228	-0.00258	0.000525	-0.000543	-0.00635*
	(0.00346)	(0.00348)	(0.00330)	(0.00353)	(0.00325)
# obsercation	7,688	7,688	7,688	7,688	7,688

Table A.12: Heterogeneous price deviation response to Google Trends by trust

This table reports the Bitcoin price deviation responses to Google Trends indices for "conflict," "crisis," "instability," and "scandal," and the heterogeneous effects by country's trust level. High-trust countries in Column (2) refer to 11 countries with Global Preference Survey (GPS) trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a trust score between -0.1 and 0.2. In Column (4), low-trust countries refer to 11 countries with a trust score below -0.1. Column (5) reports the heterogeneous response by trust level:

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the Google Trends indices for "conflict," "crisis," "instability," and "scandal." $Distrust_c$ is omitted as currency fixed effects fully absorb it. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
$GT\_Conflict$	149.784**	-32.772	253.918**	279.347*	-362.174**
	(62.977)	(41.424)	(105.588)	(152.426)	(150.654)
$GT\_Conflict \times Distrust$					8.289***
					(2.856)
GT_Crisis	67.093**	5.403	115.243	134.330**	-135.374*
	(30.762)	(19.100)	(84.639)	(51.388)	(74.394)
$GT\_Crisis \times Distrust$					3.651**
					(1.496)
$GT\_Instability$	125.198**	161.518	49.581	162.991*	250.927
	(60.100)	(126.066)	(102.548)	(83.010)	(292.271)
$GT\_Instability \times Distrust$					-1.908
					(3.995)
$GT\_Scandal$	87.498**	-29.502	177.793**	127.287*	-147.633
	(38.156)	(61.181)	(67.172)	(61.205)	(148.711)
$GT\_Scandal \times Distrust$					4.366
					(2.636)
# observations	7,688	2,728	2,232	2,728	7,688

Table A.13: Heterogeneous price deviation (from euro crypto prices) responses to Google Trends

This table reports the Bitcoin price deviation (based on euro crypto price) responses to Google Trends indices for "conflict," "crisis," "instability," and "scandal," and the heterogeneous effects by country's trust level. High-trust countries in Column (2) refer to 11 countries with Global Preference Survey (GPS) trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a trust score between -0.1 and 0.2. In Column (4), low-trust countries refer to 11 countries with a trust score below -0.1. Column (5) reports the heterogeneous response by trust level:

$$Deviation_{c,t} = \beta_1 GT_{c,t} + \beta_2 Distrust_c \times GT_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $GT_{c,t}$ denotes the Google searches in "conflict," "crisis," "instability," and "scandal." $Distrust_c$ is omitted as currency fixed effects fully absorb it. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: *Deviation*				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
$GT\_Conflict$	149.784**	-32.772	253.918**	279.347*	-362.174**
	(64.665)	(41.883)	(109.232)	(152.389)	(149.388)
$GT\_Conflict \times Distrust$					8.289***
					(2.845)
GT_Crisis	67.093**	5.403	115.243	134.330**	-135.374*
	(32.260)	(19.401)	(88.834)	(51.260)	(75.052)
$GT\_Crisis \times Distrust$					3.651**
					(1.529)
$GT\_Instability$	125.198**	161.518	49.581	162.991*	250.927
	(60.412)	(125.061)	(101.560)	(84.788)	(290.507)
$GT\_Instability \times Distrust$					-1.908
					(3.982)
$GT\_Scandal$	87.498**	-29.502	177.793**	127.287*	-147.633
	(39.698)	(60.860)	(69.264)	(61.307)	(147.589)
$GT\_Scandal \times Distrust$					4.366
					(2.615)
# observations	7,688	2,728	2,232	2,728	7,688
Currency FEs	Yes	Yes	Yes	Yes	Yes

Table A.14: Heterogeneous price deviation (from euro crypto prices) responses to institutional failures

This table reports the heterogeneous price deviation based on euro crypto price response to the institutional failure attention (IFA) index by the country's trust level from Global Preference Survey (GPS). High-trust countries in Column (2) refer to 11 countries with GPS trust scores above 0.2. Medium-trust countries in Column (3) refer to 9 countries with a GPS trust score between -0.1 and 0.2. In Column (4), low-trust countries refer to 11 countries with a GPS trust score below -0.1. Column (5) reports the test for heterogeneous response by trust level:

$$Deviation_{c,t} = \beta_1 IFA_{c,t} + \beta_2 Distrust_c \times IFA_{c,t} + \gamma_c + \epsilon_{c,t}$$

where $IFA_{c,t}$ denotes the IFA index. $Distrust_c$ is GPS trust score. The dependent variable $Deviation_{c,t}$ is the Bitcoin price deviation in Panel A and the Ethereum price deviation in Panel B. The country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) Full	(2) High-trust	(3) Mid-trust	(4) Low-trust	(5) Full
IFA	176.562**	32.481	237.020	300.584*	-218.328
	(67.356)	(37.511)	(129.739)	(158.950)	(165.465)
$IFA \times Distrust$					416.025**
					(201.880)
# observation	7,688	2,728	2,232	2,728	7,688
	PanelB: Dependent Variable $Deviation_{ETH}$				
IFA	125.101***	10.473	205.395**	199.143**	-82.600
	(42.813)	(37.129)	(77.660)	(72.696)	(129.090)
$IFA \times Distrust$					220.946*
					(128.877)
# observation	6,943	2,465	1,999	2,479	6,943

Table A.15: Trust validation with questions in the World Value Survey

This table validates the trust measure in Global Preference Survey with various questions in the World Value Survey. Panel A reports the relationship between trust and confidence in institutions, including banks, companies, government, politics, civil service, and justice. The confidence scores are calculated from the World Value Survey (WVS).

$$Confidence_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Panel B reports the relationship between trust and perceived corruption control in business, civil service, the local government, and the state government. The trust measure is from the Global Preference Survey, and the corruption control scores are calculated from the World Value Survey (WVS).

$$Corruption_c^{WVS} = Trust_c^{GPS} + \epsilon_c$$

Panel C validates the correlation between trust in the Global Preference Survey (GPS) and trust variables in the World Value Survey (WVS):

$$Trust_c^{WVS} = \beta Trust_c^{GPS} + \alpha + \epsilon_c$$

WVS's trust measures include general trust in most people, in people you know personally, in your neighbors, and in people you first met. Standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Trust and Confidence in Institutions					
	(1) Bank	(2) Companies	(3) Government	(4) Political	(5) Civil	(6) Justice
Trust	112.728**	50.835**	128.080***	108.101**	116.960***	119.257***
	(47.010)	(24.176)	(41.990)	(41.722)	(31.674)	(38.347)
# Currencies	20	27	27	27	27	26
	Panel B: Trust and Corruption in Institutions					
	Business	Civil	State	Local		
Trust	65.169**	85.103**	100.868**	69.728*		
	(30.369)	(38.997)	(44.849)	(36.374)		
# Currencies	17	17	17	17		
	Panel A: Trust Validation					
	Most Trusted	Know Personally	Neighbors	First Met		
Trust	20.923*	67.133*	60.377**	46.240		
	(10.419)	(34.239)	(26.097)	(30.653)		
# Currencies	28	23	23	23		

Table A.16: Event studies of trading volume by event type

This table reports the pre and post changes in trading volume for five types of events: political events in Column (1), government-related socioeconomic events in Column (2), government-unrelated socioeconomic events in Column (3), irrelevant events in Column (4), and unidentified Google Trends spikes in Column (5). In Panel A, the dependent variable is the Bitcoin trading volume share as a percentage of the total market trading volume. In Panel B, the dependent variable is Bitcoin trading volume growth $\Delta Volume\_Bitcoin_t = \frac{8 \times Vol\_Bitcoin_t}{\sum_{i=1}^{i=8} Vol\_Bitcoin_{t-i}}$. In Panel C, the dependent variable is the Ethereum trading volume share as a percentage of the total market trading volume. In Panel D, the dependent variable is the Ethereum trading volume growth $\Delta Volume\_Ethereum_t = \frac{8 \times Vol\_Ethereum_t}{\sum_{i=1}^{i=8} Vol\_Ethereum_{t-i}}$. As there are outliers in Ethereum trading volume for the Indian stock market crash, thus we drop this event in our analysis. Event fixed effects are included in all specifications. Robust standard deviations are clustered at the event level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable Vol_Share_{BTC}				
	(1) Political	(2) Government Economic	(3) Other Economic	(4) Irrelevant	(5) Unknown
Post	0.319	0.012	0.006	0.287	0.223
	(0.314)	(0.012)	(0.022)	(0.315)	(0.186)
# events	48	5	6	17	17
	Panel B: Dependent Variable $\Delta Vol\_Bitcoin$				
Post	8.937*	4.556	-16.886**	4.503	-10.319
	(5.062)	(7.407)	(6.226)	(11.817)	(13.544)
# events	44	4	6	15	11
	Panel C: Dependent Variable Vol_Share_{ETH}				
Post	0.006	0.054	0.072	0.052	0.0002
	(0.009)	(0.032)	(0.037)	(0.036)	(0.0002)
# events	46	4	4	15	15
	Panel D: Dependent Variable $\Delta Vol\_Ethereum$				
Post	9.457	12.609	15.305*	10.327	0.529
	(6.028)	(7.352)	(6.281)	(6.884)	(14.836)
# events	43	3	4	10	14

Table A.17: Trading volume response to institutional failures

This table reports panel regressions of trading volume on the institutional failure attention index (IFA) in Column (1) and cumulative Google keyword search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), "scandal" in Column (5). In Panel A, the dependent variable is the Bitcoin trading volume share as a percentage of the total market trading volume. In Panel B, the dependent variable is Bitcoin trading volume growth $\Delta Volume\_Bitcoin_t = \frac{8 \times Vol\_Bitcoin_t}{\sum_{i=1}^{i=8} Vol\_Bitcoin_{t-i}}$. In Panel C, the dependent variable is the Ethereum trading volume share as a percentage of the total market trading volume. In Panel D, the dependent variable is the Ethereum trading volume growth $\Delta Volume\_Ethereum_t = \frac{8 \times Vol\_Ethereum_t}{\sum_{i=1}^{i=8} Vol\_Ethereum_{t-i}}$. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable Vol_Share_{BTC}				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	0.707 (1.353)	0.480 (1.156)	0.365 (0.494)	0.720 (0.932)	-0.404 (0.714)
# observation	7,615	7,615	7,615	7,615	7,615
	Panel B: Dependent Variable $\Delta Vol\_Bitcoin$				
Google Trends	23.534 (32.465)	12.056 (18.293)	3.858 (16.238)	31.907 (38.858)	13.610 (12.891)
# observation	7,494	7,494	7,494	7,494	7,494
	Panel C: Dependent Variable Vol_Share_{ETH}				
Google Trends	0.043 (0.030)	0.048* (0.024)	0.001 (0.012)	0.024 (0.031)	-0.019 (0.027)
# observation	6,908	6,908	6,908	6,908	6,908
	Panel B: Dependent Variable $\Delta Vol\_Ethereum$				
Google Trends	7.951* (4.379)	8.284* (4.615)	3.009 (2.830)	3.044 (3.096)	3.088 (3.627)
# observation	6,869	6,869	6,869	6,869	6,869

Table A.18: Price deviation response to institutional failures with trading volume control

This table reports panel regressions of price deviation on the institutional failure attention index (IFA) in Column (1) and cumulative Google keyword search indices: "conflict" in Column (2), "crisis" in Column (3), "instability" in Column (4), "scandal" in Column (5). The trading volume control is Bitcoin trading volume growth $\Delta Volume\_Bitcoin_t = \frac{8 \times Volume\_Bitcoin_t}{\sum_{i=1}^{i=8} Volume\_Bitcoin_{t-i}}$ in Panel A and Ethereum trading volume growth $\Delta Volume\_Ethereum_t = \frac{8 \times Volume\_Ethereum_t}{\sum_{i=1}^{i=8} Volume\_Ethereum_{t-i}}$ in Panel B. Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1) IFA	(2) Conflict	(3) Crisis	(4) Instability	(5) Scandal
Google Trends	171.676**	147.441**	65.735**	112.732*	73.935*
	(70.034)	(67.589)	(30.101)	(60.970)	(43.387)
$\Delta Volume\_Bitcoin$	-1.292	-1.213	-1.135	-1.240	-1.199
	(1.093)	(1.132)	(1.141)	(1.124)	(1.162)
# observation	7,494	7,494	7,494	7,494	7,494
	Panel B: Dependent Variable $Deviation_{ETH}$				
Google Trends	114.140**	89.593*	32.577	107.543	-45.705
	(52.673)	(50.506)	(25.847)	(74.738)	(62.496)
$\Delta Volume\_Ethereum$	34.743*	34.914*	40.264**	39.358**	42.978**
	(18.179)	(18.355)	(19.054)	(18.972)	(20.416)
# observation	6,869	6,869	6,869	6,869	6,869

Table A.19: Price deviation responses to institutional failures by trading volume

This table reports the price responses to the institutional failure attention (IFA) index by different trading volume filters. Column (1) uses the full sample with non-missing price data. Column (2) further limits the regression to the sample with non-missing volume data. We further restrict our sample by quartile cutoff of trading volume: the sample with trading volume higher than the 25 percentile cutoff in Column (3), the sample with trading volume above the median trading volume in Column (4), and the sample with trading volume higher than the 75 percentile cutoff in Column (5). Country fixed effects are included in all specifications. Robust standard deviations are two-way clustered at country and week levels and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Dependent Variable $Deviation_{BTC}$				
	(1)	(2)	(3)	(4)	(5)
	All	0	25th	50th	75th
IFA	179.002**	165.876**	193.569**	111.924**	100.540**
	(68.183)	(67.266)	(73.132)	(42.313)	(44.277)
# Observation	7,688	7,615	5,711	3,805	1,893
	Panel B: Dependent Variable $Deviation_{ETH}$				
IFA	121.147***	115.720**	147.339***	140.437***	94.488**
	(43.121)	(49.484)	(42.049)	(34.732)	(41.428)
# Observation	6,943	6,908	5,258	3,499	1,775

Table A.20: Price deviation predictability in FX exchange rates

This table explores whether cryptocurrency price deviations predict anything in the currency market.

$$FX_{c,t} = \beta Deviation_{c,t} + \gamma_c + \epsilon_{c,t}$$

$FX_{c,t}$ stands for Libor-based deviations from covered interest parity (CIP) in Column (1), the future one-week exchange rate change in Column (2), the future eight-week exchange rate change in Column (3), the future 24-week exchange change in Column (4), and the dummy for significant currency depreciation in next 24 weeks (defined as 24-week currency return < -15%) in Column (5). The construction of CIP deviation follows Du et al. (2018). We construct CIP deviations for 17 out of 31 countries with Bloomberg data. Robust standard errors are reported in the parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: $FX_{c,t}$				
	(1) CIP	(2) 1-week FX Ret	(3) 8-week FX Ret	(4) 24-week FX	(5) Dummy (24-week Ret < -15%)
$Deviation_{c,t}$	3.88×10^{-8}	-0.00396	-0.00659	-0.0292	6.97×10^{-6}
	(8.96×10^{-8})	(0.00555)	(0.00785)	(0.0292)	(7.94×10^{-6})
# obsercation	4,216	7,657	7,440	6,944	6,944

B For Online Publication: Events of Google Search Peaks

We manually identify the events behind Google search peaks of the four keywords: conflict, crisis, instability, and scandal. In total, 121 spikes are found for the four keywords to verify whether the google search on "conflict," "crisis," "scandal," and "instability" reflect investors' concern for local institutional failures. 95 peaks can be found with concrete events, while we cannot identify events for the other 26 peaks. 78 spikes indicate domestic institution failures or crises, while the other 17 spikes are driven by irrelevant events (e.g., sexual scandals). This appendix documents the full list of the events found with our endeavor. Each observation represents a Google Trends peak by each currency keyword. Column "Date" provides the year-month for each event, "Short Title" refers to the event name, "Description" provides a short narrative of these events, and "Excluded" indicates whether this search peak is included in our event studies: 0 indicates the event is included in our analysis; 1 indicates this event is excluded because of lack of data; 2 indicates that the event is excluded because of too many outliers in the cryptocurrency price data as liquidity was low in earlier years. "Induce Distrust" equals 1 if a political or socioeconomic event can reduce trust in government or disappointment in the domestic economy; otherwise 0.

Events of Google Search Peaks

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
Panel A: Major Economic and Financial Crises						
ARS	crisis	2018.08	Argentine monetary crisis	Argentine peso devalued severely in 2018 because of the high inflation and capital outflow as the currency continually lost purchasing power. As a result, Argentina's government tightened the capital control on September 1, 2019. Mauricio Macri, the president of Argentina, required the companies to seek central bank permission to purchase foreign currency and to make transfers abroad. He also limited that individuals can purchase up to $10,000 US dollar per month.	0	
BRL	crisis	2014.06	Brazilian economic crisis	Brazil's economy slowed down in 2014, and the GDP decreased while the unemployment rate and inflation increased from 2014 to 2016. After 2016, a slight economic recovery began.	0	
CNY	crisis	2015.08	Chinese stock market crash	The Chinese stock market crash began on June 15, 2015. Shanghai Composite Index (SSE) continued to drop despite numerous efforts by the regulator to stop the stock market collapse. On August 24, the SSE composite index fell again by 8.48 percent, marking the largest single-day loss since 2007.	0	
Panel B: Political Scandals						
BRL	scandal	2015.12	Impeachment of Dilma Rousseff	Dilma Rousseff, the president of Brazil, was charged with criminal, administrative misconduct, and misappropriation of the federal budget on December 2, 2015. The petition also accused Rousseff of failing to act on the scandal at the Brazilian national petroleum company, Petrobras, and for failing to distance herself from the suspects in that investigation.	0	1
BRL	scandal	2018.02	Anti-Corruption Crusade Rot	On February 2, 2018, Luiz Inacio Lula da Silva, former president of Brazil, was re-elected as the Workers Party candidate for the 2018 presidential election in Sao Paulo. Lula was accused of corruption and money laundering in September 2016.	1	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
CAD	scandal	2019.03	Justin Trudeau's political scandal	Jody Wilson-Raybould, the former minister of justice and attorney general, had been pressured to help a Quebec-based construction company settle a criminal case and avoid prosecution over allegations that it bribed officials in Libya for government contracts. On March 8, 2019, it was reported that the scandal could threaten the political future of the country's leader and the governance of the Liberal Party.	2	1
GBP	scandal	2015.09	David Cameron's drug scandal	In the book "Call Me Dave," former party treasurer Lord Ashcroft made allegations of drug taking and debauchery by young Mr. David Cameron, the former prime minister of the United Kindom, on September 20, 2015. The book also claimed Lord Ashcroft, the Conservative leader, did not pay UK tax on his overseas earnings.	0	1
GBP	scandal	2016.04	Panama tax-avoidance scandal	David Cameron, the former prime minister of the United Kingdom, admitted he benefited from a Panama-based offshore trust set up by his late father on April 7, 2016. He paid income tax on the dividends, but there was no capital gains tax payable, and he said he sold up before entering Downing Street.	0	1
GBP	scandal	2018.05	Jeremy Hunt property scandal	In April 2018, The Daily Telegraph revealed that Jeremy Hunt, the former chancellor of the exchequer of the United Kingdom, breached anti-money laundering legislation by failing to declare his 50% interest in a property firm to Companies House within the required 28 days.	0	1
IDR	scandal	2019.03	Widodo bribe scandal	Muhammad Romahurmuziy, the United Development Party leader, was arrested for influence-peddling at the religion ministry. This scandal may mark the end of days for Indonesia's second-oldest political party.	0	1
INR	scandal	2016.08	Journalist murdered after a scandal report	The International Federation of Journalists (IFJ) and its affiliates, the Indian Journalists Union (IJU) and the National Union of Journalists (India) (NUJI), strongly condemned the murder of journalist Kishore Dave in Gujarat, India, on August 22, 2016. The IFJ demanded swift investigation and action to bring those responsible to justice.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
JPY	scandal	2017.02	Government land sale scandal	On February 9, 2017, the central government of Japan sold the 8,770 square meter property in Toyonaka, Osaka Prefecture, to Moritomo Gakuen for around 134 million Japanese Yen, about 14% of the land's estimated value. Separately the government paid the school 131.76 million to help decontaminate the land, reducing what the government earned to only about 2 million. As the scandal unfolded, Abe, the prime minister of Japan, resigned from her position as honorary principal in late February.	0	1
KES	scandal	2018.05-06	Kenyan anti-corruption drive	In May 2018, Kenyan authorities detained more than 50 top officials and executives after widespread public anger prompted by allegations of the theft of more than $100m at government agencies.	0	1
KRW	scandal	2016.10-11	South Korean political scandal	The 2016 South Korean political scandal involves the influence of Choi Soon-sil — the daughter of Choi Tae-min, the leader of a religious cult, over President Park Geun-Hye of South Korea. Park Geun-Hye was impeached because of this scandal.	0	1
MXN	scandal	2019.03	Odebrecht corruption	Emilio Lozoya, the former president of the state-owned oil company Petróleos Mexicanos, is accused of having requested money from scandal-plagued Brazilian construction conglomerate Odebrecht to partially finance the presidential campaign of former President Enrique Peña Nieto in exchange for contracts.	2	1
PHP	scandal	2015.07	Iglesia ni Cristo leadership controversy	In July 2015, it was reported that the Iglesia ni Cristo, an independent Nontrinitarian Christian church, had expelled some of its ministers, along with high-profile members Felix Nathaniel "Angel" Manalo and Cristina "Tenny" Villanueva Manalo, for allegedly "sowing disunity" in the Church.	0	1
RON	scandal	2017.05	Prime minister resignation	In June 2017, Sorin Grindeanu was removed from the office of prime minister by the Social Democratic Party after an internal power struggle. Afterward, Mihai Tudose, a vice-president of the Social Democratic Party, became the new Prime Minister of Romania on June 26, 2017.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
RUB	scandal	2017.02-03	Donald Trump's Russia Scandal	On February 26, 2017, the White House attempted to control public perceptions of a widening scandal over alleged contacts between aides to Donald Trump and Russian intelligence officials during the 2016 election, alleging that the FBI had dismissed reports of such links. However, with a Republican congressman calling for an independent inquiry, multiple congressional committees pursued investigations.	0	1
THB	scandal	2017.03	Corruption crackdown	At the behest of Prime Minister Prayut, the police, intelligence agencies, and the Interior Ministry have compiled a list of corrupt officers. Deputy Prime Minister Prawit Wongsuwan announced that these names would be "verified", and the legal actions will commence in February and March 2016.	0	0
UAH	scandal	2017.06	Sanction against Ukrainian separatists	The U.S. Treasury announced sanctions against 21 Ukrainian separatists on June 20, 2017.	0	1
VND	scandal	2016.08	Fish death scandal	Formosa Ha Tinh steel plant released toxic chemicals into the ocean and caused a massive amount of fish dead. Some suspect the government of a loose investigation on Formosa to protect the firm's $10.5 billion investment.	0	1
ZAR	scandal	2018.01	Gupta brothers' corruption	Atul and Rajesh Gupta, two brothers from the wealthy Gupta family, were accused in South Africa of profiting from their close links with former president Jacob Zuma and exerting unfair influence. The brothers fled to South Africa after a judicial commission began probing their corruption engagement.	2	1
AED	crisis	2017.06	Qatar diplomatic crisis	Saudi Arabia, the United Arab Emirates, Bahrain, and Egypt severed diplomatic relations with Qatar and banned Qatar-registered planes and ships from utilizing their airspace and sea routes. Saudi Arabia also blocked Qatar's only land crossing on June 5, 2017. The Saudi-led coalition cited Qatar's alleged support for terrorism as the main reason for their actions.	0	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
CLP	crisis	2019.10.	Chilean protests	Civil protests occurred throughout Chile in response to a rise in the Santiago Metro's subway fare, the increased cost of living, privatization, and inequality prevalent in the country in October 2019.	0	1
CZK	crisis	2019.12	Protest in Prague	Over 50,000 people rallied against Czech prime minister Babis. They urged Prime Minister Andrej Babis to step down over accusations he misused millions in EU funds.	0	1
GBP	crisis	2019.12	Election fallout	Following Boris Johnson's (British Prime Minister) election victory on December 12, 2019, people were concerned about how Johnson would achieve Brexit and how his government would attempt to heal the deep fractures within British politics.	0	1
HUF	crisis	2015.09	Hungary refugee crisis	Hungary closed down a key border crossing from Serbia overnight on September 14, 2015, leaving thousands of migrants stranded.	0	1
HUF	crisis	2019.12	Political crisis	Viktor Orbán, Hungary's prime minister, claimed to run a 'Christian' government; but one of his former allies, Iványi, denounced his government's consolidation of power and marginalization of minorities.	2	1
ILS	crisis	2019.12	Israeli political deadlock	Israelis would go to the polls to vote for the third time in 11 months. Any candidate who garnered the support of 61 members of the Knesset was required to form a coalition, but no one succeeded in doing so by December 11, 2019.	0	1
INR	crisis	2017.09	China–India border conflict	The 2017 China-India border conflict refers to the military standoff between the Indian Armed Forces and the People's Liberation Army of China over the Chinese construction of a road in Doklam near Donglang — a trijunction border area.	0	1
KES	crisis	2017.06	Kenya terrorist attacks	The five new deaths reported in Mandera brought the total number of Kenyans killed in the suspected Al Shabaab attack to 40. Government lacks preparation to fight against terrorism attacks.	1	1
KRW	crisis	2019.12	North Korea pressure	North Korea announced that the country would launch an "important experiment" of a missile-engine site before December 31, 2019, a deadline set by the political leader, Kim Jong-un.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
MXN	crisis	2019.12	Mexico–Bolivia diplomatic crisis	Juan Evo Morales Ayma, president of Bolivia from 2006 to 2019, and two cabinet members flew to Mexico on November 10, 2019, where they were offered political asylum. After that, Mexican President called Morales's resignation illegal and refused to recognize the new government of Jeanine Áñez. However, Bolivia claims that Mexico violated the UN Declaration on Territorial Asylum.	0	1
PHP	crisis	2017.07	Marawi crisis	Moro Islamic Liberation Front members used the ceasefire to repatriate civilians. However, ISIL-linked militants fired in areas occupied by government military forces. When the unilateral ceasefire expired, full-scale hostilities continued between government forces and militants.	0	1
PHP	crisis	2017.11-12	Marawi crisis	An Amnesty International report released on November 16, 2017, blamed the militants and government forces for widespread abuses, some of which amount to war crimes.	0	1
PKR	crisis	2015.03	India-Pakistan Conflict	India–Pakistan border skirmishes were a series of armed clashes and exchanges of gunfire between the Indian Border Security Force and the Pakistan Rangers in the disputed Kashmir region and the borders of Punjab. On 14th February 2015, A sixty-year-old villager was killed, and the event escalated the military tension.	1	1
PLN	crisis	2017.11	Ethnic purity	Around 60,000 people marched in Warsaw on Independence Day (November 12, 2017), some chanting anti-Semitic, anti-Muslim, and anti-gay slogans.	0	1
PLN	crisis	2019.12	Leave-EU proposal	The country's Supreme Court has warned that Poland could have to leave the European Union over the judicial reform proposal on December 17, 2019.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
RON	crisis	2019.12	No-confidence vote	Romania's government lost a no-confidence vote, leading to the end of governance on October 10, 2019. A transitional government was expected to take over the country's governance until the next national election in 2020.	0	1
RUB	crisis	2017.03-04	Anti-corruption Protests	On March 26, 2017, roughly 60,000 people participated in anti-corruption protests across 80 Russian towns and cities. Hundreds of protesters were detained, including opposition leader Alexei Navalny and employees of the Anti-Corruption Foundation.	1	1
RUB	crisis	2017.11-12	Anti-corruption Protests	In Moscow, many police were present, and the Okhotny Ryad station was closed to avoid mass-scale protests. Police detained about 112 people on the night of November 6, 2017.	0	1
SAR	crisis	2017.11-12	Saudi Arabian purge	Crown Prince Mohammad bin Salman formed a committee to fight against corruption. Several prominent Saudi Arabian princes, government ministers, and business people were arrested in Saudi Arabia on November 4, 2017.	0	1
ARS	conflict	2017.12	Argentina Dirty War	Argentina's court granted house arrest to 88-year-old Miguel Etchecolatz, the former police officer who worked for the military dictatorship of the 1970s, for crimes against humanity in December 2017.	0	1
BRL	conflict	2017.12	Land conflicts	Deforestation is widespread in the Brazilian state of Rondônia, deep in the western Amazon rainforest. On December 1, 2017, a new investigation by Greenpeace revealed that deforestation of protected areas had risen in the state. Indigenous communities viewed deforestation as a massive threat to their disappearing homeland. And as budget cuts depleted resources to protect these communities, many were worried this conflict between industrialization and indigenous communities would worsen further.	1	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
COP	conflict	2017.04	Sign of Peace Accord	The Revolutionary Armed Forces of Colombia (FARC) signed a peace accord in 2016 and demobilized its armed force in 2017. While 13,185 FARC members were formally demobilized, about 800 of them rejected the peace accord entirely and refused the demobilization.	1	1
CZK	conflict	2015.11-12	Anti-Islam rally	Milos Zeman, the President of the Czech Republic, attended a rally against refugees and Islam in Prague on 17 November 2015 on the anniversary of the 1989 Velvet Revolution.	0	1
CZK	conflict	2017.12	Rising Czech populism	European far-right leaders gathered in Prague for a controversial conference likely to confront protests from groups who fear rising xenophobic populism in the Czech Republic.	1	1
IDR	conflict	2015.12	Papua conflict	The abundance of natural resources in West Papua generated continuing conflict, making it one of Asia's sorest spots regarding human rights violations. One article on December 15, 2015, discussed the human rights crisis in West Papua.	1	0
PKR	conflict	2016.01	Quetta suicide bombing	A suicide bomber detonated himself near a polio center near Quetta, Pakistan, killing at least 15 people and wounding another 25 in January 2016. Both Tehrik-i-Taliban Pakistan and Jaishul Islam organizations claimed responsibility.	1	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
PKR	conflict	2019.02	India–Pakistan border skirmishes	In February 2019, Indian jets crossed the international border to conduct air strikes on an alleged JeM camp in the Khyber Pakhtunkhwa province of Pakistan.	0	1
PLN	conflict	2017.11	Ethnic purity conflict	Around 60,000 people marched in Warsaw on Independence Day (November 12, 2017), some chanting anti-Semitic, anti-Muslim, and anti-gay slogans.	1	1
RON	conflict	2019.03	Romania's politician jailed	Liviu Dragnea, the leader of Social Democratic Party (PSD), was sentenced to three and a half years of imprisonment for corruption on May 27, 2019.	2	1
RUB	conflict	2017.12	Syrian civil war	At the end of December 2017, the Russian government announced that its troops would be deployed to Syria permanently.	1	0
THB	conflict	2017.12	Thailand's southern conflict	One article on December 27, 2017, stated that 235 people died in 2017 due to clashes between the Muslim-Malay insurgents and Thai troops and police, according to numbers collected by Deep South Watch.	0	1
THB	conflict	2019.03	Senate composition controversy	Thailand's military government failed to create conditions for a free and fair national election in March 2019. The junta-appointed Senate hold roughly 50% of the total votes, severely undermining Thai citizens' right to choose their leaders.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
UAH	conflict	2017.12	Ukraine crisis	Ukraine and separatist rebels in the east of the country have exchanged hundreds of prisoners in one of the biggest swaps since the conflict began in 2014.	0	1
UAH	conflict	2015.08	The conflict between Ukraine troops and pro-Russian separatists	News reports that a third member of Ukraine's national guard died from injuries after Monday's violent protests outside the parliament in Kyiv on August 31, 2015.	0	1
UAH	conflict	2016.01-02	Ukraine domestic conflict	According to BBC news in February 2016, Ukraine remained gripped by corruption, and little progress had been made in improving the economy. Conflicts in the Donbas with pro-Russian separatists further added economic uncertainties.	0	1
COP	instability	2016.07	Ceasefire deal	On June 23, 2016, the Colombian government and the Revolutionary Armed Forces of Colombia (FARC) rebels signed a historic ceasefire deal, bringing them closer to ending more than five decades of conflict.	0	0
ILS	instability	2017.08	Palestinian missile attack on Israel	Around 9 pm on August 8, 2015, one missile was launched from Gaza (a Palestinian city). It fell inside Israel in an open area near Ashkelon.	0	1

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
RUB	instability	2018.10	Amnesty researcher mock execution	On October 6, 2018, Oleg Kozlovsk, an Amnesty International researcher, was abducted, beaten, and threatened with death by people who identified themselves as officers of the local Center for Combating Extremism, a special police unit in Russia.	0	1
SAR	instability	2017.08	Qatar–Saudi Arabia diplomatic conflict	On August 24, 2017, Qatar announced that it would restore full diplomatic relations with Iran. As the diplomatic standoff reached its second year, Saudi Arabia announced it would build a canal and turn Qatar into an island.	0	0
Panel C: Other socioeconomic Events						
AED	crisis	2019.12	UAE economy first-ever drop	On December 5, 2017, Bloomberg reported that the U.A.E. economic output growth slowed, and unemployment surged.	0	1
AUD	crisis	2015.06	Migrant crisis	Australia detained any migrant and refugee trying to reach its shores, took them to offshore processing camps, and resettled them elsewhere.	0	0
BRL	crisis	2017.11-12	Sovereign credit rating downgraded	Brazil lost its investment-grade rating after Fitch became the second credit agency to downgrade the country's debt to junk grade on December 16, 2017. Fitch cited concerns about economic and political crises threatening to topple President Dilma Rousseff.	0	1
BRL	crisis	2019.12	Trump's steel tariffs	Trump imposed tariffs on Brazil on December 3, 2019.	0	0
COP	crisis	2015.08	Peso depreciation	As the petroleum industry in Colombia is an important contributor to the country's economy, the peso depreciated sharply against the U.S. dollar as the oil price declined.	0	1
GBP	crisis	2017.11	Homeless crisis	Meg Hillier, a British Labour and Co-operative politician, claimed that the government's approach to tackling the homelessness problem was an "abject failure" on December 20, 2017.	0	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
INR	crisis	2015.06	Indian milk crisis	Both private and cooperative dairies were rejecting milk from small dairy farmers in Andhra Pradesh. Meanwhile, milk procurement prices have been reduced, and farmers poured milk down the drain in June 2015.	0	0
INR	crisis	2019.12	Severe slowdown	The government made an ambitious policy goal for double-digit growth and propelled India into a $5 trillion economy by 2024-2025. However, India's gross domestic product (GDP) growth dropped to 4.5% in the third quarter of 2019, making the policy goal to be an implausible mission.	0	1
KES	crisis	2019.12	Kenya food crisis	In December 2019, Crisis and Stressed outcomes persist due to ongoing recovery from the 2018/19 drought and the negative impact of recent floods and landslides on household food and income sources.	0	0
KES	crisis	2019.06	Drought in Africa	On June 15, 2019, a news article discussed precipitation shortages across eastern Africa, southern Africa, and the Horn of Africa; and altered another dire season for farmers. The drought would increase food prices and drive up the need for international aid to people who lived in the three regions.	1	0
PKR	crisis	2019.12	Balance of payments crisis	In December 2019, Pakistan implemented belt-tightening measures to ease a balance of payments crisis.	1	0
ZAR	crisis	2018.01	Cape Town water crisis	The Cape Town water crisis in South Africa was a severe water shortage in the Western Cape region, most notably affecting the City of Cape Town. In mid-January 2018, previous Cape Town Mayor Patricia de Lille announced that the City would be forced to shut off most of the municipal water supply if conditions continued.	1	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded	Induce Distrust
ZAR	crisis	2019.12	South African energy crisis	The South African energy crisis, a period of national-level rolling blackouts as electricity shortage, destabilized the national power grid. South Africa experienced its worst energy crisis, and Load Shedding Stage 6 was activated for the first time in December 2019.	0	0
BRL	instability	2016.03	Zika virus	In February 2016, World Health Organisation declared a global public health emergency following an outbreak of the Zika virus in Brazil.	1	0
INR	instability	2016.02	Indian stock market crash	By 16 February 2016, the Bombay Stock Exchange (BSE) had seen a fall of 26% over the past eleven months, losing 1,607 points in four consecutive days.	0	1
Panel D: Irrelevant Events						
AED	scandal	2015.07	Ambassador 1MDB scandal	On June 30, 2017, the Wall Street Journal reported that companies connected to Yousef Al Otaiba, the United Arab Emirates ambassador, received $66 million allegedly misappropriated from 1Malaysia Development Berhad.	0	
AUD	scandal	2018.03-04	Ball-tampering scandal	A scandal surrounded the Australian national cricket team. In March 2018, television cameras caught Cameron Bancroft trying to rough up one side of the ball with sandpaper to make it swing in a match against South Africa at Newlands.	0	
CAD	scandal	2015.09	VW diesel emissions scandal	In September, the Environmental Protection Agency (EPA) found that many VW cars sold in America had a “fraudulent device/software” in diesel engines that could cheat the emissions tests in the United States.	0	
KRW	scandal	2019.03	K-Pop sex scandal	Seungri (Lee Seung-Hyun), a former member of the South Korean band BIGBANG, appeared at the police station on March 14, 2019. He was questioned over the charges of facilitating prostitution services.	0	

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded
MXN	scandal	2015.09	VW diesel emissions scandal	In September, the Environmental Protection Agency (EPA) found that many VW cars sold in America had a "fraudulent device/software" in diesel engines that could cheat the emissions tests in the United States.	0
PKR	scandal	2015.08	Child sexual abuse scandal	On August 10, 2015, the parents of victims in a horrific child sexual abuse scandal said that the Pakistan police tried to downplay the scale of crimes committed.	0
PKR	scandal	2019.11	Spot-fixing scandal	Pakistan cricketer Mohammad Asif apologized for his involvement in a 2010 betting scandal and admitted his spot-fixing role.	0
RON	scandal	2015.09	VW diesel emissions scandal	In September, the Environmental Protection Agency (EPA) found that many VW cars sold in America had a "fraudulent device/software" in diesel engines that could cheat the emissions tests in the United States.	0
SEK	scandal	2015.09	Swedish jet scandal	In September 2015, Financial Times revealed that many business ethical scandals in which executives enjoyed inappropriate perks in Sweden, such as hunting lodges, business jets, and reimbursing each others' expenses.	0
SEK	scandal	2017.04	Swedish elk-hunting scandal	The chairman of Handelsbanken, often regarded as one of Europe's most respected banks, has become the latest senior Swedish business figure caught up in the scandal over elk hunting hospitality.	0
SEK	scandal	2018.03	Swedish academy scandal	72-year-old Jean-Claude Arnault, the former artistic director of the cultural center Forum, was accused of sexual misconduct.	0
SEK	scandal	2018.12	Swedish academy scandal	In early December 2018, Jean-Claude Arnault was found guilty by a Stockholm court of rape against one woman and sentenced to two years and six months in prison.	0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded
VND	scandal	2019.03	Food safety scandal	Dozens of kindergarteners in the northern Vietnamese province of Bac Ninh have tested positive for pork tapeworm in less than a month. Their parents blamed dirty school meals for the mass infection of unprecedented scale in March 2019.	0
AUD	crisis	2019.12	Australia's bushfire crisis	Record-low rainfall contributed to severe bushfires that burned more than 5 million hectares.	0
CAD	crisis	2019.12	Climate crisis	Justin Trudeau's newly re-elected government will decide whether to approve the construction of the largest open-pit oil sands mine in Canadian history. If approved, the mine would be a huge environmental threat.	0
CHF	crisis	2017.11	Rohingya crisis	Switzerland urged joint efforts to resolve the Rohingya crisis on November 21, 2017.	0
PHP	crisis	2019.12	Christmas typhoon	Christmas Typhoon caused 20 death in the Philippines.	0
Panel E: Unknown Events					
ARS	scandal	2019.8			0
HRK	scandal	2015.01			1
ILS	scandal	2015.09			0
JPY	scandal	2016.03			0
SAR	scandal	2015.07			0
ZAR	scandal	2016.05			0
CHF	crisis	2019.12			0
JPY	crisis	2017.04			1
SEK	crisis	2019.12			0
SEK	crisis	2017.11-12			0
THB	crisis	2016.11			0

Events of Google Search Peaks (Continued)

Currency	Keyword	Date	Short Title	Description	Excluded
CZK	conflict	2016.11-12			0
PHP	conflict	2018.08-09			1
PHP	conflict	2019.08-09			0
VND	conflict	2017.12	(best guess) Vietnam War		0
CHF	instability	2018.05			0
SEK	instability	2019.12			0
SEK	instability	2017.11-12			0
ZAR	conflict	2016.02			0
ZAR	conflict	2017.02			0
ZAR	conflict	2018.02			1
ZAR	conflict	2019.02			0
ZAR	conflict	2020.02			1

C For Online Publication: Limits of Arbitrage

In this section, we discuss various frictions in cryptocurrency trading. Price deviations can reflect the underlying cross-country Bitcoin demand only if the law of one price fails. We empirically give content to the sources of friction and provide a quantitative evaluation. We propose return asynchronization to measure the magnitude of frictions under the assumption that arbitrage is more challenging if the domestic Bitcoin returns are less correlated with the Bitcoin dollar returns. The return asynchronization is defined as 100 minus correlation (in percent) between the Bitcoin returns in local currency, and the Bitcoin U.S. dollar returns in a rolling window of eight weeks.

$$Asyn_c = 100 - Corr(Ret_c^{BTC}, Ret_{USD}^{BTC})$$

where Ret_c^{BTC} is the Bitcoin return in local currency and Ret_{USD}^{BTC} is the U.S. dollar return. A higher return asynchronization implies more disconnection with the international Bitcoin market, in other words, more friction to arbitrage.The average return asynchronization across all countries is 24.67%, and the standard deviation is 29.33%. Among the 31 countries, Saudi Arabia has the highest average return asynchronization at 44.99%, while Japan has the lowest average at 1.73%. We first characterize the relationship between return asynchronization and price deviation at the country level. First, Bitcoins are more expensive in markets with higher friction. Figure C.1 plots the relationship between the average return asynchronization and average price deviation by currency. One percentage point increase in asynchronization corresponds to an average 11.57 bps (*s.e.*=2.95, R-squared = 0.20) higher price deviation. A higher price premium can incentivize arbitragers to sell more Bitcoins to the country. Second, more frictions also correspond to a more volatile price. Figure C.2 checks a relationship between the average return asynchronization and the standard deviation of price deviation by currency. These two measures yield a 12.68% correlation (*s.e.*=2.05).

In the remaining section, we evaluate how different types of friction correlate with cross-country variation in return asychronization. Investors face various restrictions or costs on cross-country arbitrage, at least in the short run. An arbitrager needs to complete the following these steps to take advantage of the price difference across the market:

1. Convert the U.S. dollar into Bitcoin through a crypto-exchange;

2. Send Bitcoin from the exchange wallet to a private wallet;

3. Send Bitcoin from a private wallet to an exchange where the arbitrager can sell Bitcoin for local currency directly;

4. Sell Bitcoin for local currency;

5. Transfer funds from a local crypto exchange to a local bank account;

6. Convert local currency back to the U.S. dollar and remove the money from the local country.

Many barriers can arise in this procedure and prevent arbitragers from acting, thus, leading to a positive-sloping Bitcoin supply curve in the short run. It is often argued in the literature that capital controls (Step 6) are the primary reason for the price deviations across countries in the literature.[38] We start with capital controls—the conventional explanation—then examine crypto-fiat liquidity, market segmentation, and legal risks.

C.1 Capital Controls

Since September 2019, Argentine companies have been subject to a central bank rule that requires them to repatriate all export earnings back and convert those earnings into pesos at the official exchange rate set by the central bank. Further, companies have been subject to central bank approval to access the U.S. dollar. Simultaneously, as shown in Figure A.1, the Argentine Bitcoin price surged to 40% more expensive than the dollar price while the central bank tightened the capital controls in Argentina.

Under tight capital controls, arbitragers would face more challenges when sending money out of the country or might not convert local currencies to the U.S. dollar at a desirable exchange rate. Following Fernández et al. (2016), we classify all countries into three categories: Open (least restrictive), Gate, and Wall (most restrictive). Small retail arbitragers face cross-border money transfer costs if they want to take advantage of price differences.

[38] See:Makarov and Schoar (2019),Makarov and Schoar (2020), Yu and Zhang (2022), and Choi et al. (2022)

We proxy retail transfer costs with the exchange rate margin charged by the vendor recommended by *Monito.com* and the average margin and transaction fee recorded by the World Bank Remittance Survey.[39]

Table C.1 correlates the average return asynchronization with the capital controls and retail transaction costs. Return asynchronization is higher in countries with more restrictive capital controls: 10.4% for 20 "Gate" countries and 14.9% for five "Wall" countries. However, as reported in Columns (1) and (2), no more than 11.54% of variation can be explained by the capital control measure. Moreover, we do not find retail transfer costs correlate with the return asynchronization, as shown in Columns (3) - (6). Our findings confirm that capital controls matter but do not explain such considerable variation in asynchronization.

C.2 Insufficient Liquidity

But why do we see price deviations even in countries with the free capital flow? For example, Sweden imposes little capital control and is labeled as "Open" in Fernández et al. (2016). However, the Swedish Bitcoin price is 5.82% higher than the dollar price, and its returns are only 75% correlated with the dollar returns. The first conjecture is the shortage of liquidity. The total trading volume in Sweden was only 1,214 BTC in 2019, while the trading volume in U.S. dollar was 16,702,356 BTC.[40] Arbitragers either fail to find enough Bitcoin buyers in Sweden or cannot sell many Bitcoins without lowering the Sweden Krona price.

We explore whether the trading volume can explain the cross-country variation in return asynchronization. Figure C.3 plots the average return asynchronization and log Bitcoin trading volume in 2019. One unit increase in log volume predicts a 2.88 ($s.e.$=0.55) decrease in return asynchronization. The R-squared is 54.78%.

[39] Money transfer costs are only available for some money corridors from local countries to the United States. Thus, we use the transfer costs of corridors from the United States to other countries instead.

[40] The real trading volume can be even lower than the data shows. Cong et al. (2022) implies that crypto exchanges frequently use wash trading to fake volume.

C.3 Segmented Trading Markets

Then, we dive into the market structure of cryptocurrency trading. In Sweden, investors typically trade cryptocurrencies through peer-to-peer OTC platforms, such as LocalBitcoins and Bisq.[41] Arbitragers can only sell a tiny number of Bitcoin at a time; for example, the order size per advertisement ranged from 150 to 1,200 SEK on October 8, 2020.

Cross-currency arbitrage can be costly even in countries with exchanges to facilitate trading. Korea has six active cryptocurrency exchanges: Huobi Korea, GOPAX, Korbit, Coinone, UPbit, and Bithumb Korea. However, all these exchanges only have active trading in Korean Won—almost no investors buy or sell with US dollars. Arbitragers must send Bitcoins from a US exchange to a Korean exchange and typically pay various transaction fees: Binance charges 0.04% to withdraw Bitcoin, and Coinbase charges 1.49% for fiat currency transactions in the U.S.[42,43] Sending Bitcoin across address typically would take 10-60 minutes to complete, depending on the blockchain network's congestion. Arbitragers have to bear the risk of price changes during this period.

To quantify cryptocurrency market segmentation, we manually collected trading volume in the last 24 hours from the top 100 crypto exchanges (ranked by CryptoCompare) on June 10, 2020, and only 75 were active. We compute volume share as the number of Bitcoin traded in one currency divided by the total Bitcoin traded on the same exchange. Then, we define the primary trading pair as the currency with the highest volume share. Figure C.4 counts the number of exchanges by the volume share of the primary trading pair. 37 out of the 75 exchanges, de facto, only execute trading in one unique currency. Multi-currency trading is only active listing platforms or OTC markets without automated market-making; for example, Localbitcoins and Bisq are the two exchanges in the bracket "20-40%" trading volume from the primary trading pair.

Trading volume depletes if we look beyond the primary currency used in the exchange. Figure C.5 summarizes the average volume share of the top 5 active trading pairs. The

[41] OTC platforms allow users to post the quantity and quote in any fiat currency without a market-making system. Thus, these OTC markets tend to provide many fiat-crypto trading pairs, although liquidity is limited.

[42] See: https://www.binance.com/en/fee/depositFee

[43] See: https://help.coinbase.com/en/coinbase/trading-and-funding/pricing-and-fees/fees

primary currency accounts for 87.9% of the total volume. The number rapidly drops to 8.8% for the second functional currency, 2.2% for the third, 0.8% for the fourth, and 0.3% for the fifth. It is challenging to implement arbitrage across currencies within one exchange.

For each country, we count how many exchanges officially accept its fiat currency for cryptocurrency purchases (although the actual volume can be zero). Figure C.6 plots the average return asynchronization by the number of exchanges allowing trading in the currency. The average return asynchronization is 38.76% for the 8 currencies with no coverage in the top 100 exchanges. The number decreases to 26.39% for the 7 countries with only one exchange, 21.10% for the 6 countries with 2 to 3 exchanges, 17.80% for the 5 countries with 4 to 5 exchanges, and 10.85% for the 6 countries with more than 5 exchanges.

C.4 Laws and Regulations

In September 2017, China announced its plan to crack down on cryptocurrency exchanges, and Bitcoin trading volume in China plummeted by over 99%. Figure C.7 shows the rise of return asynchronization after the ban became effective in November.[44] Since September 2017, the return asynchronization rose from around 5% to 80% until April 2018. We use the return asynchronization in Hong Kong as a placebo, and it does not respond to the Chinese ban.

Regulations can occur at any stage of the arbitrage. Holding and trading cryptocurrency might be unlawful; regulators can crack down on exchanges; withdrawals of fiat money crypto exchanges might be subject to capital taxation or anti-money laundering scrutiny. Different countries have different regulations and legal statuses for cryptocurrency. We manually code cryptocurrency regulations from *Regulation of Cryptocurrency Around the World report* compiled by The Law Library of Congress. Appendix D details the laws and regulations of the 31 countries in our sample. The most crucial dichotomy is whether cryptocurrency trading is legal or not. The United Arab Emirates, Pakistan, and Vietnam explicitly defined cryptocurrency as unlawful. Colombia, China, Indonesia, Pakistan, Saudi Arabia, and Thailand implicitly banned or announced policies against cryptocurrencies.[45]

[44] See Auer and Claessens (2018) for a comprehensive event study of 151 regulatory events on crypto-assets.
[45] A standard implicit ban that targets crypto exchanges is to forbid domestic banks from opening bank

We further look into countries where crypto-trading is legal and investigate their efforts to combat tax evasion and anti-money laundering. Australia, Canada, Switzerland, Czech Republic, Japan, and Korea enacted anti-money laundering laws specific to cryptocurrencies; Argentina, Brazil, the United Kingdom, Israel, Kenya, Mexico, Sweden, and South Africa issued anti-money laundering warnings. Argentina, Australia, Canada, Switzerland, the United Kingdom, Israel, Japan, Poland, Romania, Russia, Sweden, and South Africa proposed tax laws for cryptocurrency trading.[46]

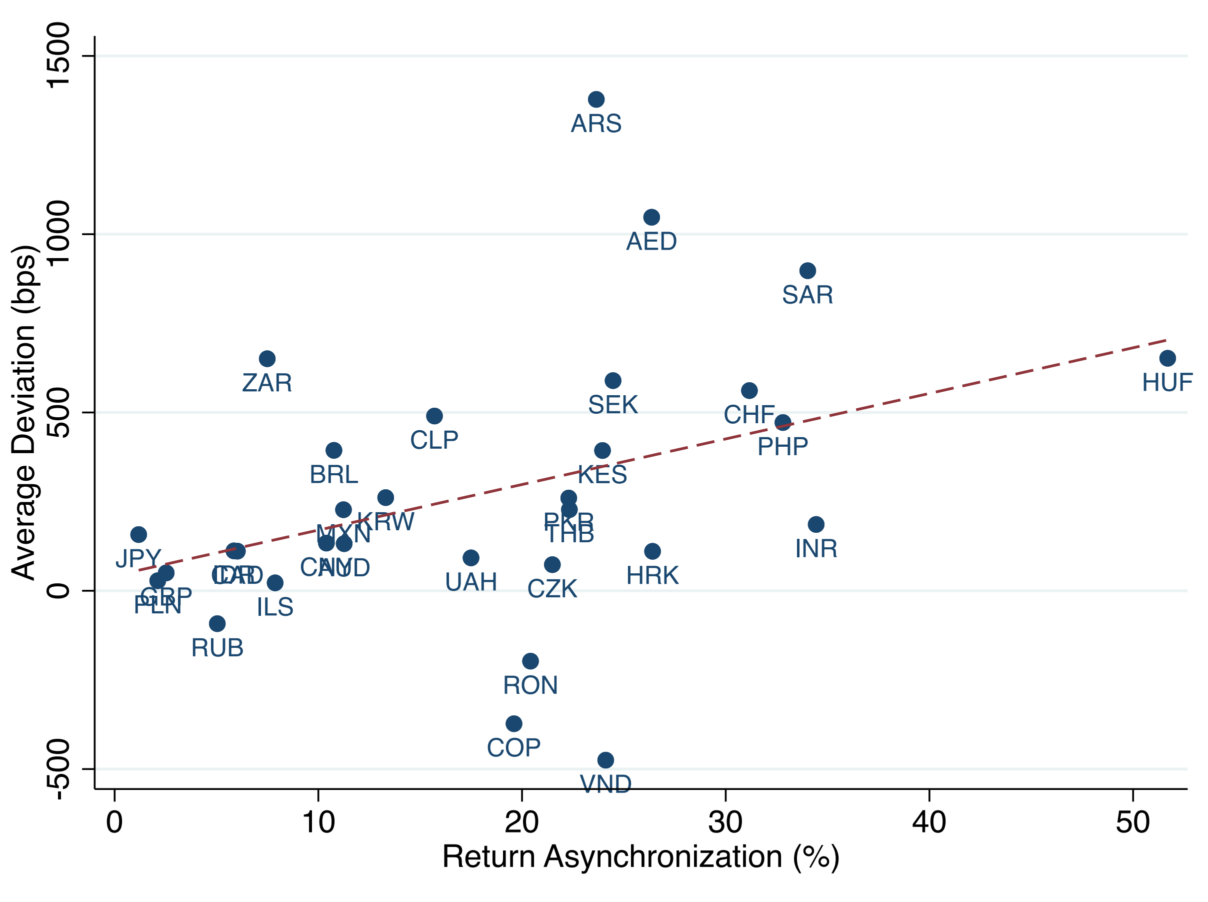
Table C.2 reports the relationship between return asynchronization and regulations. Of 31 countries, 6 countries do not impose cryptocurrency regulations by 2020. Column (1) implies the 6 unregulated countries experience 6.05% (*s.e.* = 4.42%) higher return asynchronization on average. Within the 25 countries with regulations, Column (2) shows cryptocurrency bans (implicit and explicit pooled) raise return asynchronization by 5.89% (*s.e.*= 1.80%) on average. Unregulated markets and crypto-bans make it difficult to find reliable exchanges to convert fiat currency into and out of cryptocurrencies. Columns (3) and (4) evaluate tax and anti-money laundering laws. Return asynchronization decreases by 6.55% (*s.e.*= 3.79%) and 2.42% (*s.e.* = 3.96%), respectively. Figure C.8 plots return asynchronization by regulatory regimes. Most countries below 10%—Russia, South Africa, Israel, Canada, Japan, Poland, and Pakistan—recognize Bitcoins as a legal investment and collect tax on them.[47]

accounts for crypto exchanges. Exchanges cannot receive fiat money from investors; thus, investors cannot easily trade through exchanges. There are many ways to circumvent the restrictions on bank accounts, such as working with foreign banks or building an OTC market. Note that the OTC platforms are hard to ban as OTC platforms do not need to interact with the local banking system. Investors on OTC platforms send fiat currency to their trading counterpart's bank account directly. Thus, we still find trading activities even after countries banned Bitcoin.

[46]For each country, we also record the date of the cryptocurrency ban, tax law, and anti-money laundering laws. Most regulations started to crowd in after the Bitcoin price reached 1000 dollars in 2017.

[47]India is the only exception where Bitcoin is officially banned. However, domestic investors can still purchase Bitcoins with Rupee from many vendors. See:https://www.buybitcoinworldwide.com/india/.

Figure C.1: Return asynchronization and average Bitcoin price deviation

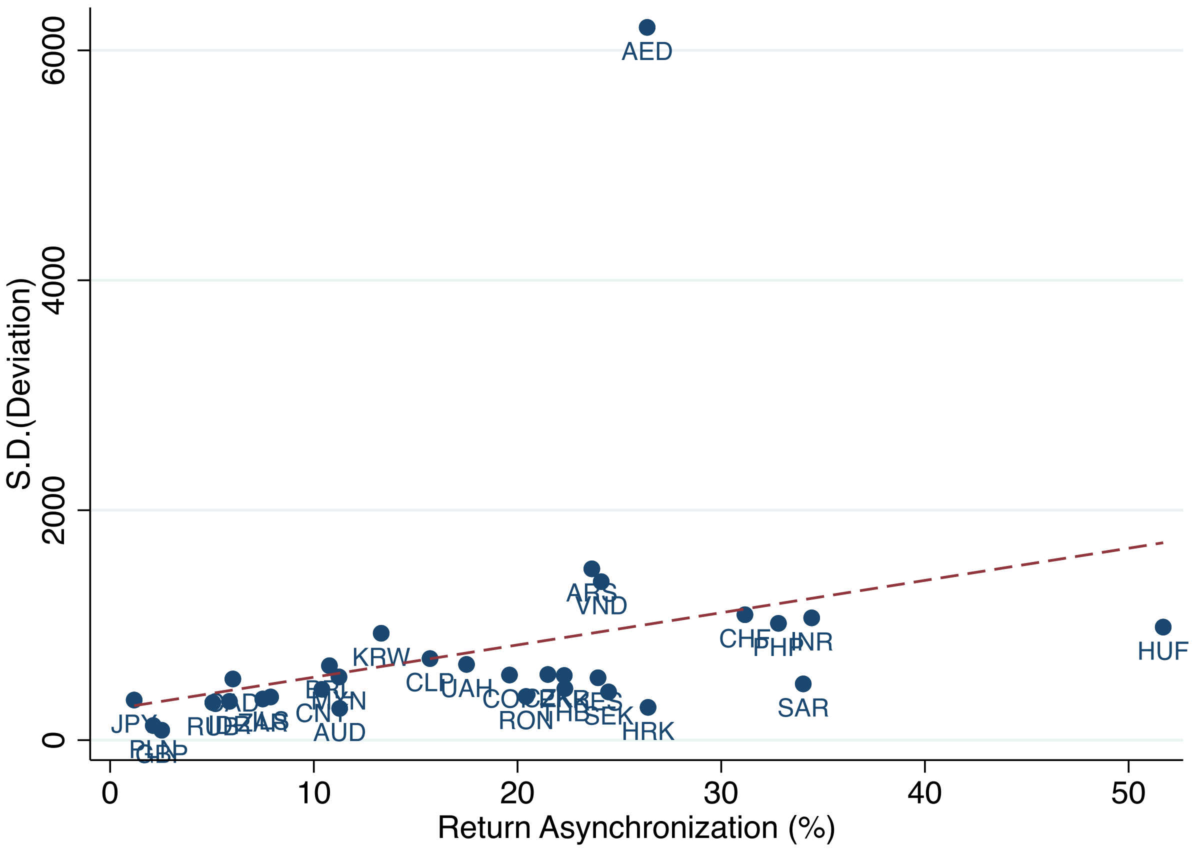


Notes: This figure shows the relationship between the average return asynchronization and the average price deviation by currency.

$$\overline{Deviation_c} = \beta \overline{Asyn_c} + \epsilon_c$$

where $\overline{Deviation_c}$ is the average price deviation, and $\overline{Asyn_c}$ is the average return asynchronization in country c.

Figure C.2: Return asynchronization and standard deviations of price deviations

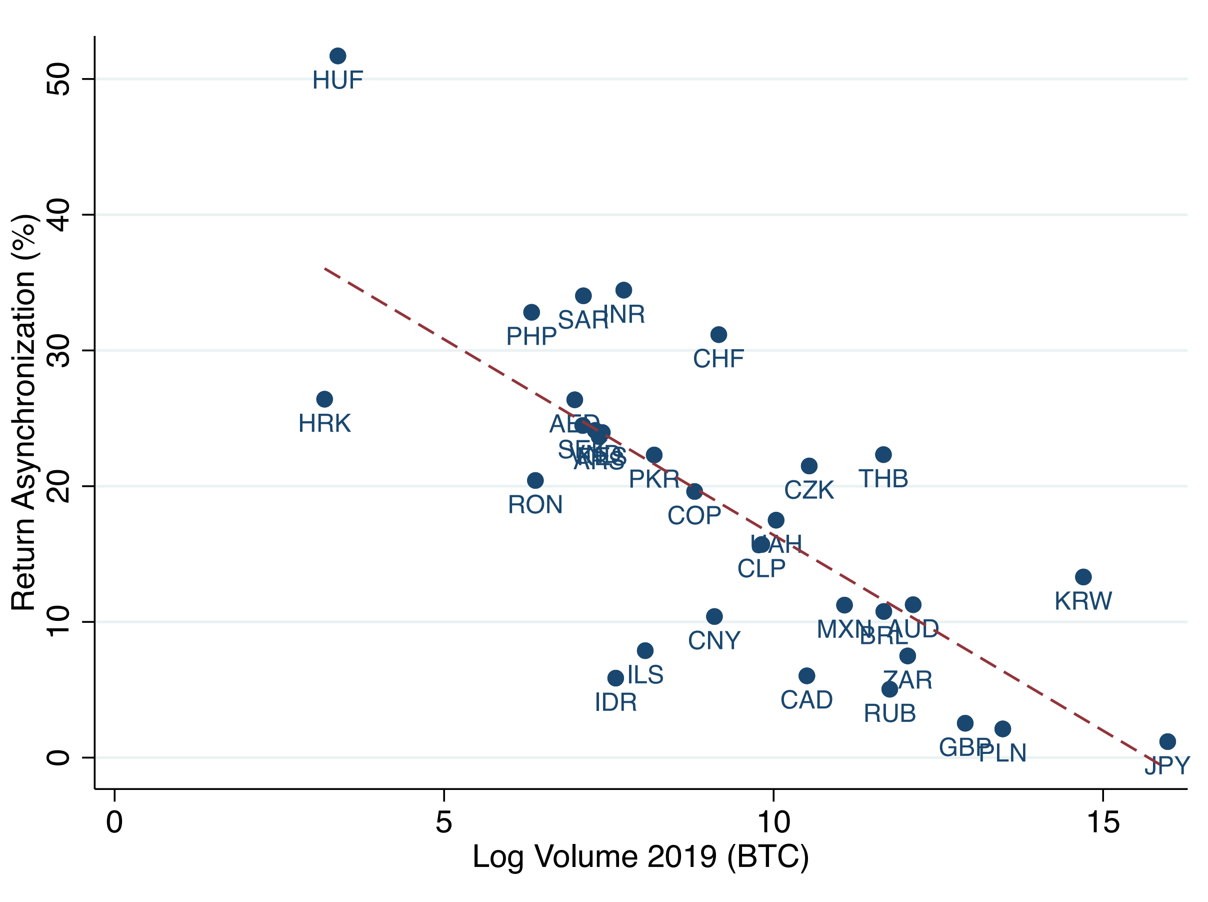


Notes: This figure shows the positive relationship between the average return asynchronization and the standard deviation of price deviations by currency.

$$SD(Deviation_c) = \beta\overline{Asyn_c} + \epsilon_c$$

where $SD(Deviation_c)$ is the standard deviation of price deviation, and $\overline{Asyn_c}$ is the average return asynchronization in country c.

Figure C.3: Return asynchronization and liquidity

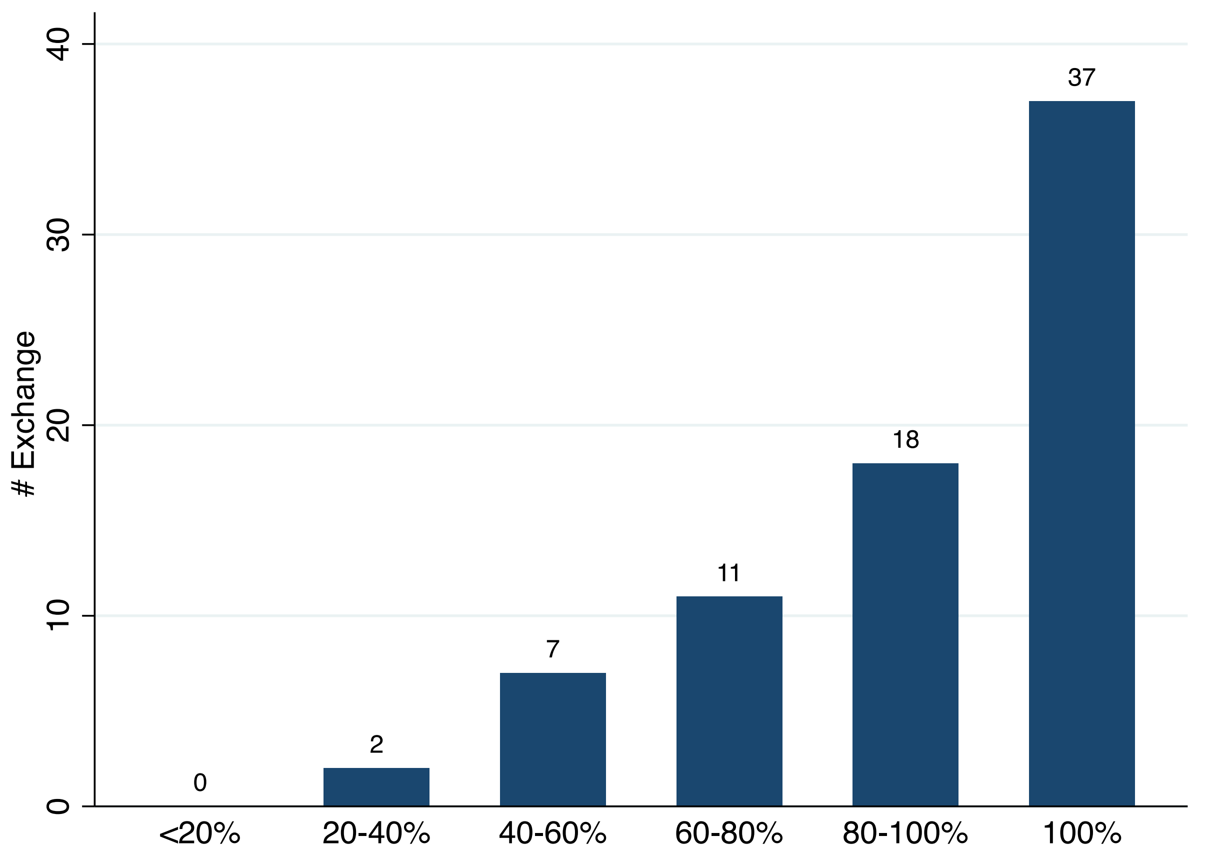


Notes: This figure plots the average return asynchronization and log trading volume in 2019.

$$\overline{Asyn_c} = \beta Log\_Vol_c + \epsilon_c$$

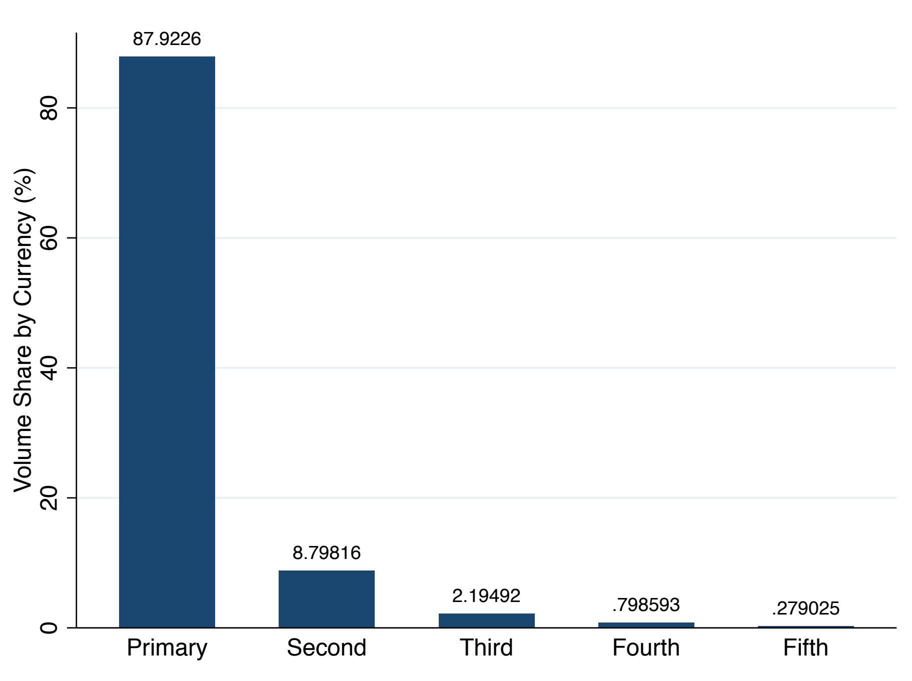
where $\overline{Asyn_c}$ is the average return asynchronization of country c, and Log_Vol_c is the log number of Bitcoins traded in 2019.

Figure C.4: Exchanges by volume share of primary trading pair



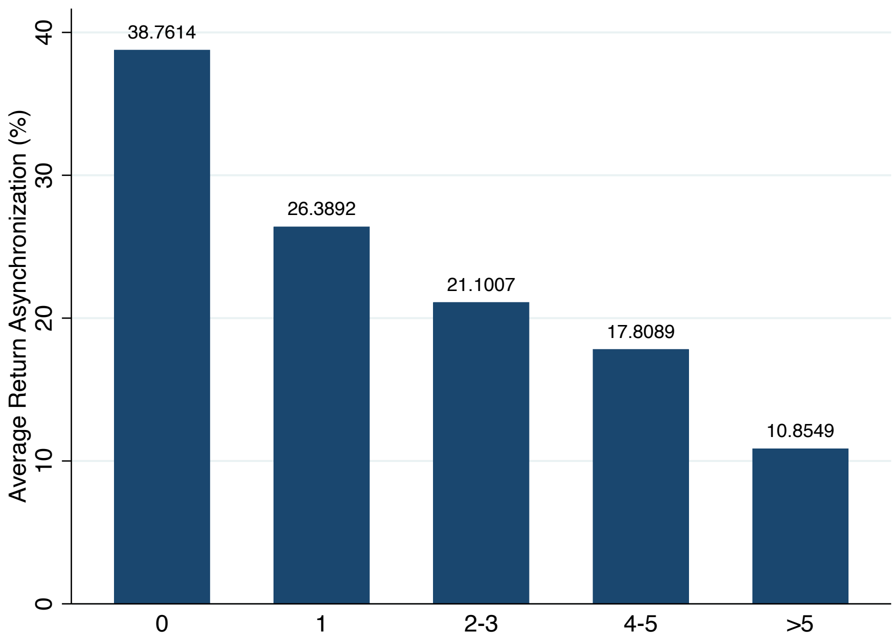
Notes: This figure plots the number of exchanges sorted into six categories by the primary trading pair's volume share. 37 out of 75 exchanges have only one fiat currency actively traded. The two "20-40%" exchanges are peer-to-peer listing platforms (trading happens outside the exchange): Localbitcoins and Bisq.

Figure C.5: Average volume share in top 5 trading pairs



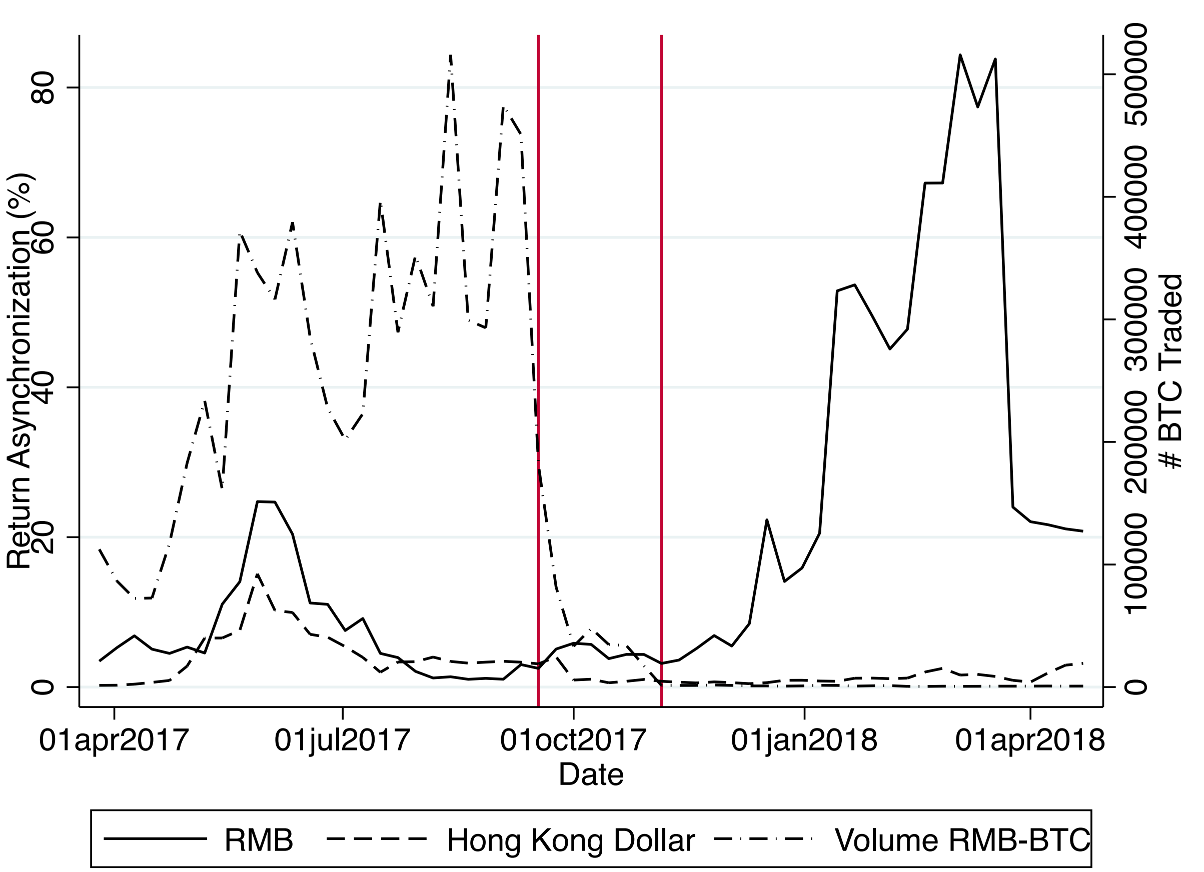
Notes: This figure plots the average volume share of the top 5 most active traded fiat currencies (with Bitcoin). The primary trading pair accounts for 87.9% of the total trading volume. The number sharply decreases to 8.80% for the second, 2.19% for the third, 0.80% for the fourth, and 0.28% for the fifth active fiat currency.

Figure C.6: Average return asynchronization and number of top exchanges by currency



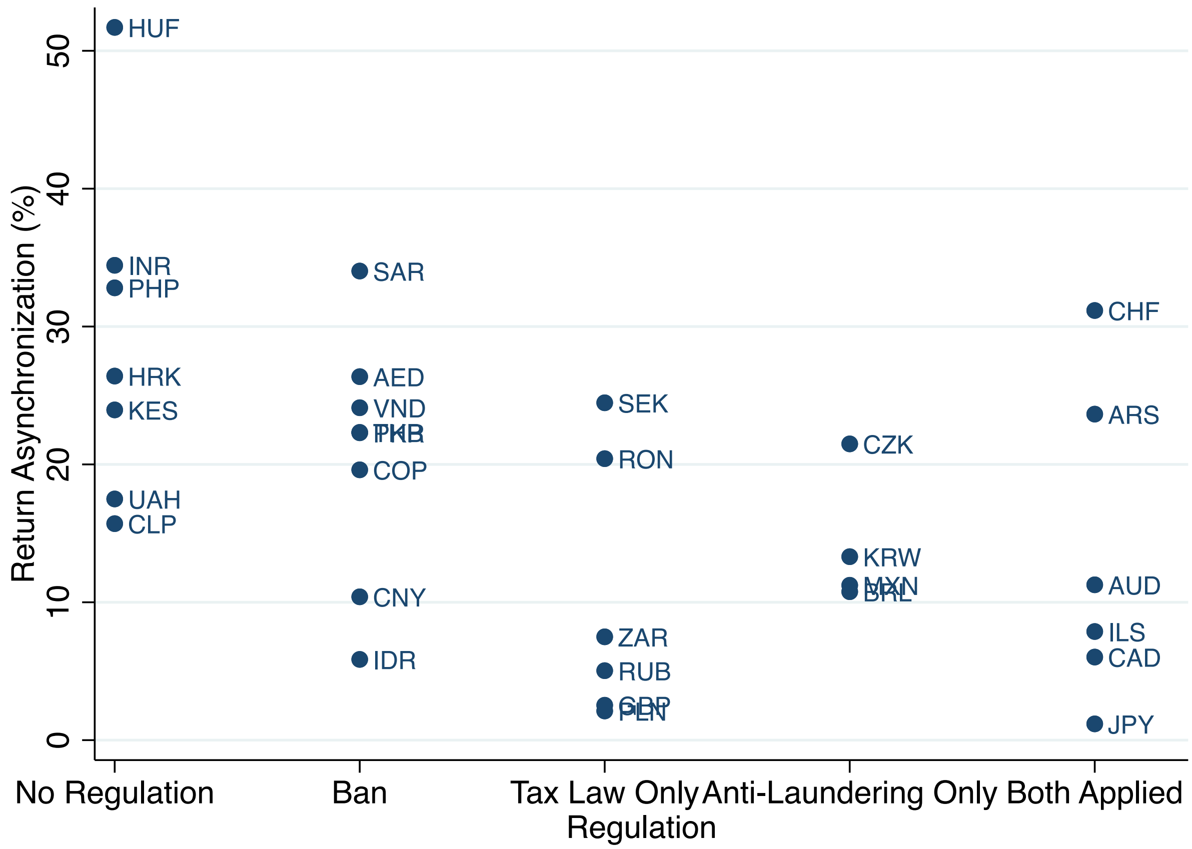
Notes: This figure plots the average return asynchronization against the number of exchanges with fiat trading pair by currency. For the eight currencies with no top 100 exchanges covering their fiat currency, the average return asynchronization is 38.76%. The return asynchronization decreases to 26.39% for the seven currencies with one exchange, 21.10% for the six currencies with two or three exchanges, 17.80% for the five currencies with 4 to 5 exchanges, and 10.85% for the six currencies with more than five exchanges.

Figure C.7: Return asynchronization before and after China Ban



Notes: In September 2017, China started its plan to shut down cryptocurrency exchanges in the country. All cryptocurrency exchanges in Beijing and Shanghai were ordered to submit plans for winding down their operations by September 20, 2017. Leading crypto exchanges started to stop trading at the end of the month, followed by Huobi and OKCoin. Chinese authorities decided to ban digital currencies as part of a plan to reduce financial risks. The weekly trading volume (dash-dotted line) of Bitcoin drops from 450885.96 (Sep 10, 2017) to 33387.74 (Oct 1, 2017), to 1373.24 (Nov 5, 2017). The solid line is the return asynchronization between Chinese RMB Bitcoin returns and US dollar returns. The dashed line is the return asynchronization between Hong Kong dollar Bitcoin returns and US dollar returns.

Figure C.8: Return asynchronization and law



Notes: This figure shows the relationship between return asynchronization and law across countries. There are five law status categories: "No regulation," "Ban," "Tax Law Only," "Anti-Money Laundering Law Only," and "Both Applied."

Table C.1: Return asynchronization and capital controls
This table reports the impacts of capital controls and retail money transfer costs on return asynchronization. The capital control measure is from Fernández et al. (2016): In Column (1), we assign 1 to the "Open" category, 2 to the "Gate" category, and 3 to the "Wall" category. In Column (2), the "Open" category is the missing group; i.Gate and i.Wall are two indicators for the "Gate" and "Wall" categories. Retail transfer costs are collected from Monito.com and the World Bank remittance survey. Columns (3) and (4) report the results based on data from Monito.com, and Columns (5) - (6) report the results based on data from the World Bank remittance survey. The exchange rate margin refers to the markup paid to the service provider per unit of funds transferred. The transaction fee refers to the fixed cost per transaction the service provider charges.

$$\overline{Asyn_c} = \beta X_c + \gamma + \epsilon_c$$

where $\overline{Asyn_c}$ is the average return asynchronization in country c, and X_c refers to capital control or retail transfer cost. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Return Asynchronization					
	Capital Controls		Retail Transfer Costs			
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Controls	7.240**					
	(3.268)					
i.Gate		10.352*				
		(5.533)				
i.Wall		14.936**				
		(6.530)				
Exchange Rate Margin			0.694		-2.422	
			(2.091)		(2.814)	
Transaction Fee				-0.591		-0.254
				(0.891)		(0.396)
R-squared	11.54%	12.83%	0.49%	0.93%	6.62%	3.00%
# Currencies	31	31	29	29	12	12

Table C.2: Return asynchronization and regulations

This table reports the relationship between return asynchronization and regulations. We classify the regulatory status into four categories. "Regulate or not" dummy is one of the countries that have any specific regulation for cryptocurrency; otherwise, zero. "Legal Status" dummy is one if regulators ban cryptocurrency; otherwise, zero. The "Tax Laws" dummy is one if tax laws apply to cryptocurrency; otherwise, zero. "Anti-Money Laundering" dummy is one of the countries that announces anti-money laundering laws for cryptocurrency; otherwise, zero.

$$\overline{Asyn_c} = \beta Law_c + \epsilon_c$$

where $\overline{Asyn_c}$ is the average return asynchronization in country c. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Return Asynchronization (%)			
	(1)	(2)	(3)	(4)
Regulateornot	-6.052			
	(4.423)			
LegalStatus		5.892***		
		(1.796)		
TaxLaws			-6.546*	
			(3.788)	
Anti-MoneyLaundering				-2.421
				(3.964)
#Currencies	31	24	24	24

D For Online Publication: Law and Regulations

We collect data on the cryptocurrency regulatory framework across countries from the Law Library of Congress. Global Legal Research Directorate at the Law Library of Congress surveys the legal and policy landscape towards cryptocurrency worldwide in 2018. For each country, it documents the progress of cryptocurrency regulation and law. We manually search for the legal status, tax laws, and anti-money laundering laws for every country in our sample. Besides, we collect the announcement dates of cryptocurrency bans, tax laws, and anti-money laundering laws.

In the following table, Column (2) reports the legal status: 1 = implicit ban, 2 = absolute ban, 0 = no info. Column (3) reports tax laws: 1= yes, 0 = no info. Column (4) report anti-money laundering-related regulations: 1= warning, 2 = implicit yes, 3= absolute yes, 0= no info. Columns (5)-(8) report the announcement dates of these corresponding regulations.

Law and Regulation

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
AED	2	0	0	Jan, 2017			Under article D.7.3 of the Regulatory Framework for Stored Values and an Electronic Payment System, issued by the Central Bank of the United Arab Emirates in January 2017, all transactions in “virtual currencies” (encompassing cryptocurrencies in Arabic) are prohibited.
ARS	0	1	2		Dec, 2017	Jul, 2014	The amendment to the Income Tax Law on December 29, 2017 provides that the profit derived from the sale of digital currency will be considered income and taxed as such.
AUD	0	1	3		May, 2016	Apr, 2018	The government guided the tax treatment of cryptocurrencies in May 2016, and Australian Taxation Office (ATO) followed with a set of actions. Regarding anti-money laundering and counterterrorism financing (AML/CTF), the government introduced a bill in Parliament in August 2017, and the relevant provisions came into force on April 3, 2018.
BRL	0	0	2				On November 16, 2017, the Brazilian Federal Reserve Bank (Banco Central do Brasil) issued Notice No. 31,379, alerting citizens to the risks arising from the virtual currencies’ trading and custody.
CAD	0	1	3		Mar, 2017	Jun, 2014	On June 19, 2014, the Governor General of Canada consented to Bill C-31, which includes amendments to Canada’s Proceeds of Crime (Money Laundering) and the Terrorist Financing Act. The new law treated virtual currencies, including Bitcoin, as “money service businesses” for the anti-money laundering law.

Law and Regulation (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
CHF	0	1	3				In September 2017, FINMA closed down the unauthorized providers of the fake cryptocurrency “E-Coin”, liquidated the companies, and issued a general warning about fake cryptocurrencies to investors. Furthermore, three other companies were put on FINMA’s warning list due to suspicious activity and eleven investigations were conducted into other presumably unauthorized business models relating to such coins.
CLP	0	0	0				
CNY	1	0	0	Sep, 2017			On September 4, 2017, seven central government regulators — the PBOC, the Cyberspace Administration of China (CAC), the Ministry of Industry and Information Technology (MIIT), the State Administration for Industry and Commerce (SAIC), the China Banking Regulatory Commission (CBRC), the China Securities Regulatory Commission (CSRC), and the China Insurance Regulatory Commission (CIRC) — jointly issued the Announcement on Preventing Financial Risks from Initial Coin Offerings, which banned initial coin offerings (ICOs) in China.
COP	1	0	0	Jun, 2017			The Superintendencia Financiera (SF) (Financial Superintendency) of Colombia warned in June 2017 circular that bitcoin is not a currency in Colombia and therefore may not be considered legal tender susceptible to canceling debts.

Law and Regulation (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
CZK	0	0	3			Nov, 2014	Amendments have been made to the Czech Republic's anti-money laundering legislation, making it also applicable to persons providing services related to virtual currencies, i.e. those who buy, sell, store, manage, or mediate the purchase or sale of virtual currencies or provide other services related to such currencies as a business law on November 14 2016.
GBP	0	1	1		Mar, 2014		For unincorporated businesses, income tax is chargeable to the profits and losses that can be attributed to cryptocurrency transactions. The UK also taxes the earnings of transactions in which a gain is realized after a transaction with cryptocurrencies if an individual user buys and sells coins as an investor.
HRK	0	0	0				
HUF	0	0	0				
IDR	1	0	0	Jan, 2018			On January 13, 2018, Bank Indonesia (Indonesia's central bank) released a statement that warns against buying, selling, or otherwise trading in virtual currencies.
ILS	0	1	2		Jan, 2018	Feb, 2018	Although virtual currencies are not recognized as actual currency by the Bank of Israel, the Israel Tax Authority has proposed that the use of virtual currencies should be considered as a "means of virtual payment" and subject to taxation.
INR	0	0	0				On April 6, 2018, the RBI issued a notification prohibiting banks, lenders and other regulated financial institutions from "dealing with virtual currencies".

Laws and Regulations (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
JPY	0	1	3		Dec, 2017	2017 (Month Unknown)	Under the Act on Prevention of Transfer of Criminal Proceeds, cryptocurrency exchange businesses are obligated to check the identities of customers who open accounts, keep transaction records, and notify authorities when a suspicious transaction is recognized. According to the National Tax Agency (NTA), the profit earned by sales of cryptocurrency is, in principle, considered miscellaneous income, rather than capital gains. The NTA compiled questions and answers regarding the tax treatment of cryptocurrency and posted it online on December 1, 2017.
KES	0	0	1				
KRW	0	0	3		Jun, 2018	Jul, 2017	Under the Act on Reporting and Using Specified Financial Transaction Information, financial institutions are required to report financial transactions that are suspected, based on reasonable grounds, to be illegal or to involve money laundering July 26, 2017.
MXN	0	0	2			Aug, 2018	Mexico has enacted a law extending the application of its laws regarding money laundering to virtual assets, thereby requiring financial institutions that provide services relating to such assets to report transactions exceeding certain amounts.
PHP	0	0	0				
PKR	2	0	0	Feb, 2018			The Federal Investigation Agency (FIA) has launched operations against the people dealing in the cryptocurrencies.
PLN	0	1	0		Apr, 2018		On April 4, 2018, the Ministry of Finance published guidance on the tax effects of trading in cryptocurrencies.

Law and Regulation (Continued)

Currency	Legal Status	Tax Laws	Anti-money laundering	Ban Date	Tax Law Date	Anti-money laundering Law Date	Note
RON	0	1	0		Mar, 2018		In March of 2018 the National Agency for Fiscal Administration reportedly declared that income from transactions with cryptocurrencies are taxable.
RUB	0	1	0		Jul, 2018		It is expected that the legislative framework for cryptocurrency regulation will be enacted by July 1, 2018, after which the rules on the taxation of cryptocurrency operations will be introduced.
SAR	1	0	0	Jul, 2018			The Saudi Arabian Monetary Agency (SAMA) has issued a warning on July 4, 2017 against Bitcoin because it is not being monitored or supported by any legitimate financial authority.
SEK	0	1	1		Apr, 2015		In 2015 the Swedish Tax Authority published a guideline on how it will view and tax mined bitcoins for the 2014 tax year.
THB	1	0	0	Feb, 2018			The Bank of Thailand issued a circular on February 12, 2018, asking financial institutions to refrain from doing any business involving cryptocurrencies.
UAH	0	0	0				
VND	2	0	0	Oct, 2017			The State Bank of Vietnam issued a decree on cryptocurrency on October 30, 2017.
ZAR	0	1	1		Apr, 2018		On April 6, 2018, the South African Revenue Services (SARS) issued a clarification on the tax status of VCs.